Applications of Probabilistic Logic Programming

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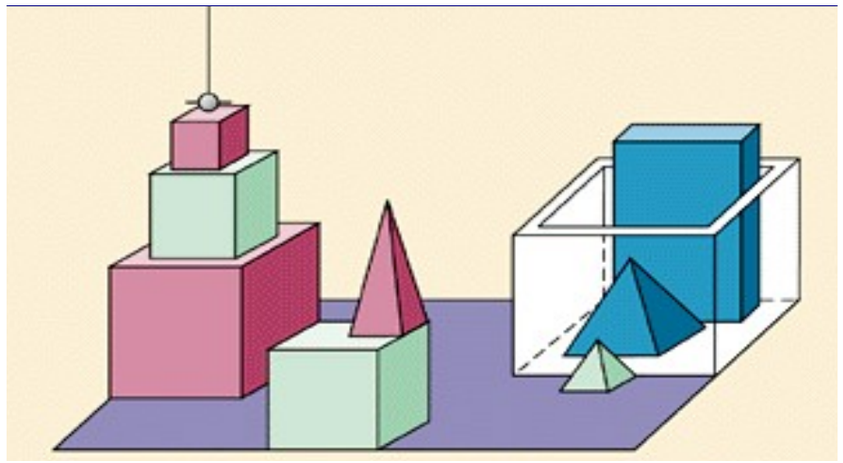
ILP 2015, Kyoto

SHRDLU [Winograd]

- Artificial Intelligence
  - the endeavor to make intelligent machines.
- Early days 1970s-1980s
  - focus on high-level reasoning
  - model driven
- limitations
  - assuming perfect knowledge about the world
  - assumed a deterministic world
  - no learning (from data)



SHRDLU

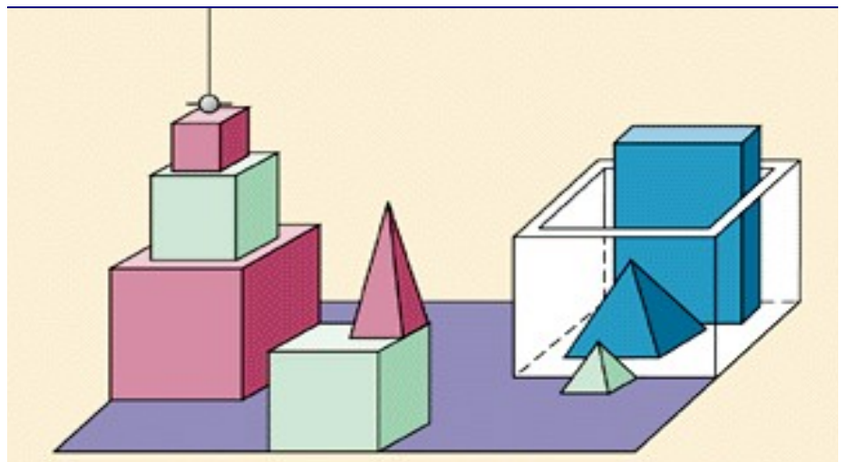


diagram adapted from Winograd, Understanding Natural Language (1972)

Person: Pick up a big red block.
Computer: OK.
Person: Grasp the pyramid.
Computer: I don't understand which pyramid you mean.
Person (changing their mind): Find a block which is taller than the one you are holding and put it into the box.
Computer: By "it", I assume you mean the block which is taller than the one I am holding.
Computer: OK.
Person: What does the box contain?
Computer: The blue pyramid and the blue block.
Person: What is the pyramid supported by?
Computer: The box.
Person: How many blocks are not in the box?
Computer: Four of them.
Person: Is at least one of them narrower than the one which I told you to pick up?
Computer: Yes, the red cube.
etc.

Historical perspective

- Next phase in AI 90s-00s
  - focus on processing low-level sensory information
  - *probabilistic graphical models, neural networks, svms* in vision, robotics, natural language processing ...
  - *data-driven* - uses data to learn
  - coping with *uncertainty*
  - limitations
    - lack of high-level reasoning
    - does not deal with objects and relations
    - has a hard time to deal with knowledge

Now is the time

- to integrate these two views
  - the technology is getting ready
  - the applications demand it
  - and it is happening
- I believe the key challenge for Artificial Intelligence is to bridge the gap between low-level perception and high-level reasoning

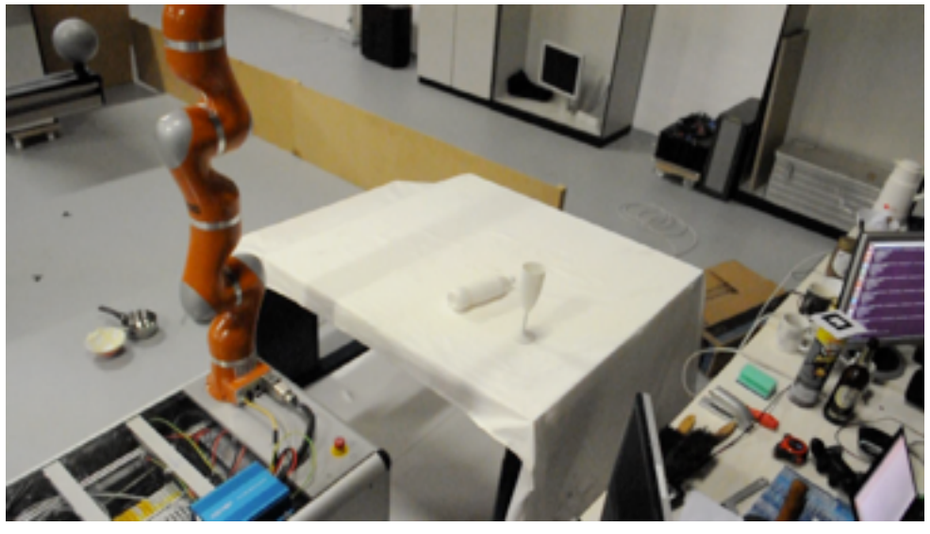
Why is this relevant ?

Bring me the tea pot and the sugar

The Robot Grasping Task

Object:pan
Part:handle
Task:P&P on table

Object:bottle
Part:top
Task:pass



Object:bottle
Part:middle
Task:Pass

Object:cup
Part:top
Task:Pour out

The Robot Grasping Task

Object:pan
Part:handle
Task:P&P on table

Object:bottle
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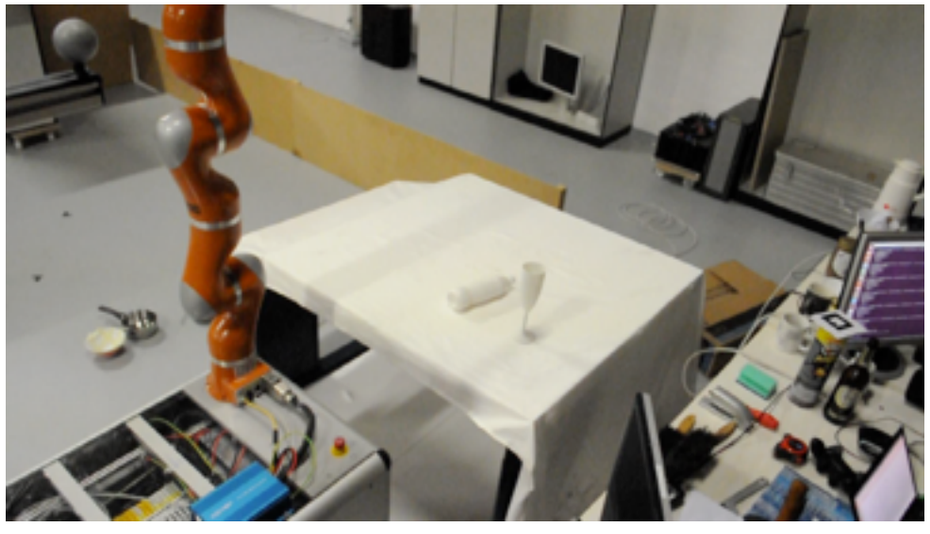
Task:pass



Object:bottle
Part:middle
Task:Pass

Object:cup
Part:top
Task:Pour out

This requires dealing with

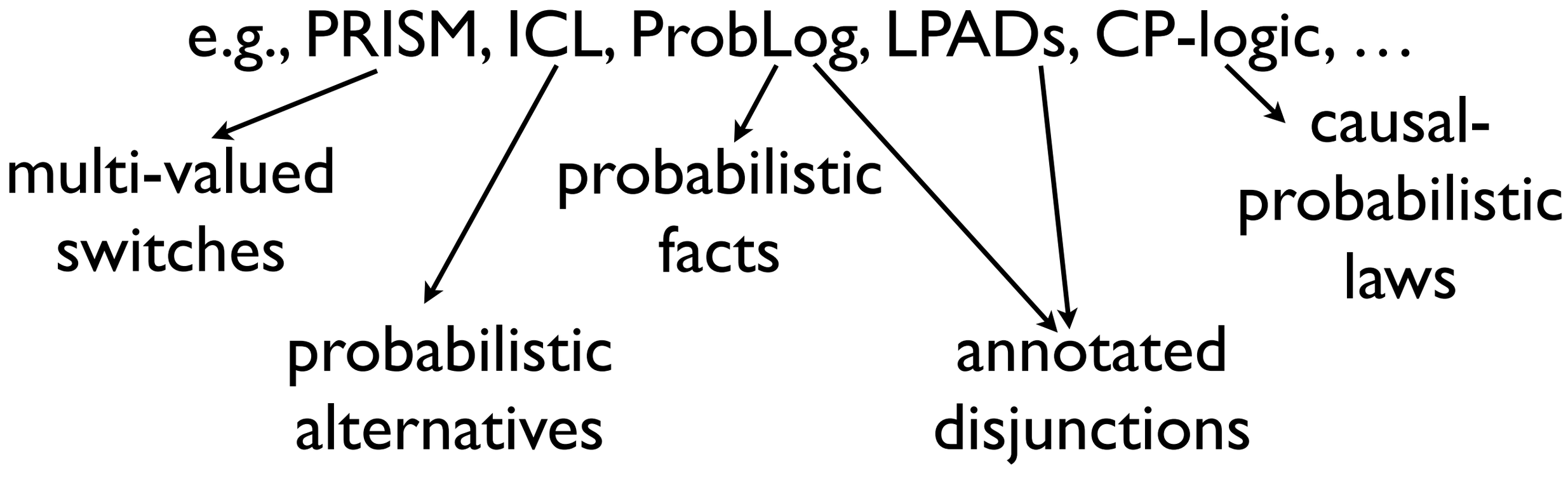
- Structured environments
  - objects, and
  - relationships amongst them
- and possibly
  - using background knowledge
- cope with uncertainty
- learn from data

Statistical Relational Learning
Probabilistic Logic Programming

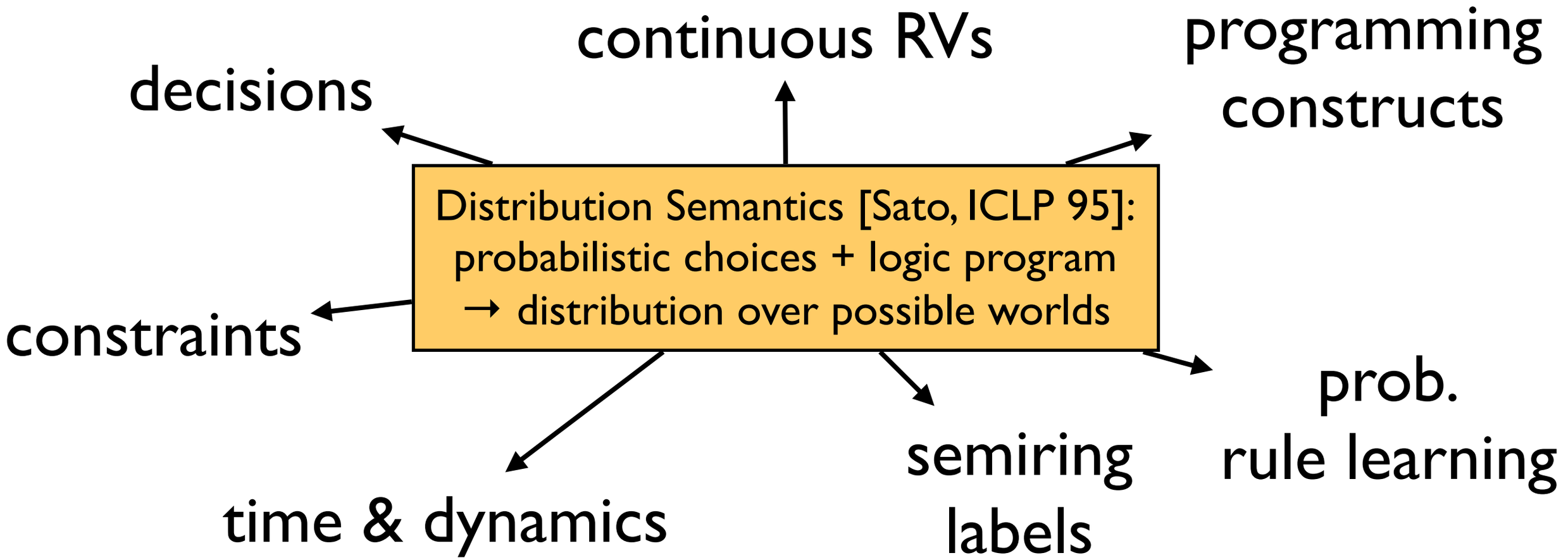
Probabilistic Logic Programming

Distribution Semantics [Sato, ICLP 95]:
probabilistic choices + logic program
→ distribution over possible worlds

OVERVIEW paper [Kimmig, De Raedt, MLJ 15]



Extensions of basic PLP



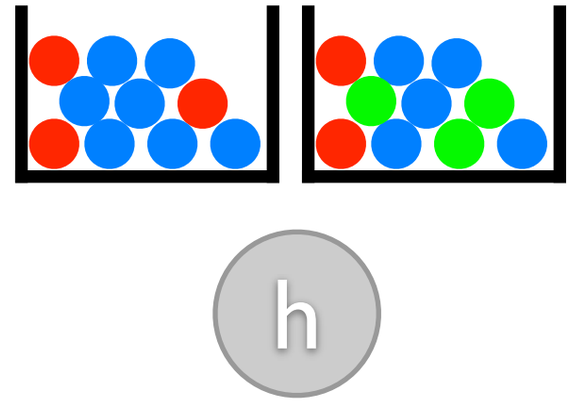
Overview

- Extensions motivated by applications
  - Distributional clauses — continuous distributions for use in robotics
  - Dynamics — for use in robotics and planning
  - Decision Theoretic ProbLog for biological network inference
  - Probabilistic rule learning — use with NELL
  - Semiring labels — kernels
- *Focus on ProbLog / kLog line of research at KU Leuven*

PART 1: Recap PLP

ProbLog by example:

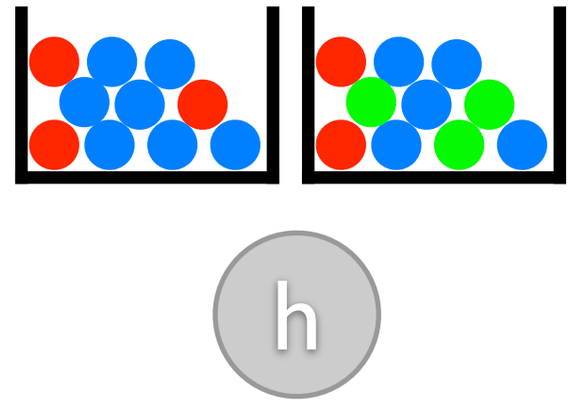
A bit of gambling



- toss (biased) coin & draw ball from each urn
- win if (heads and a red ball) or (two balls of same color)

ProbLog by example:

A bit of gambling



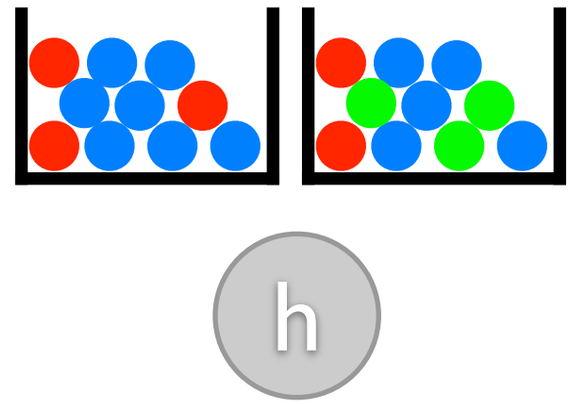
- toss (biased) coin & draw ball from each urn
- win if (heads and a red ball) or (two balls of same color)

```
0.4 :: heads.
```

probabilistic fact: heads is true with probability 0.4 (and false with 0.6)

ProbLog by example:

A bit of gambling



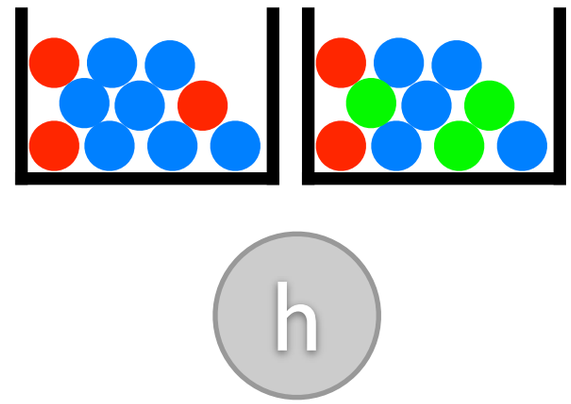
- toss (biased) coin & draw ball from each urn
- win if (heads and a red ball) or (two balls of same color)

```
0.4 :: heads.
0.3 :: col(1,red); 0.7 :: col(1,blue) <- true.
```

annotated disjunction: first ball is red with probability 0.3 and blue with 0.7

ProbLog by example:

A bit of gambling



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- win if (heads and a red ball) or (two balls of same color)

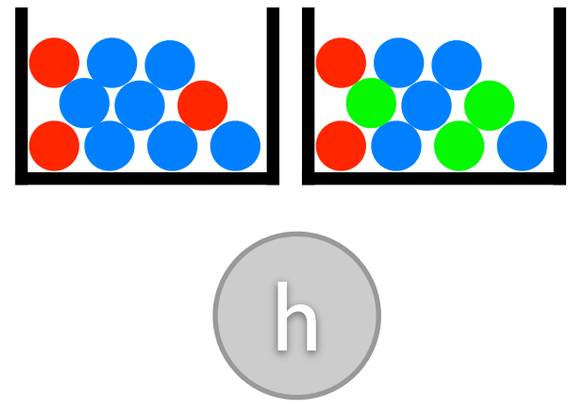
```
0.4 :: heads.

0.3 :: col(1,red); 0.7 :: col(1,blue) <- true.
0.2 :: col(2,red); 0.3 :: col(2,green);
                   0.5 :: col(2,blue) <- true.
```

annotated disjunction: second ball is red with probability 0.2, green with 0.3, and blue with 0.5

ProbLog by example:

A bit of gambling



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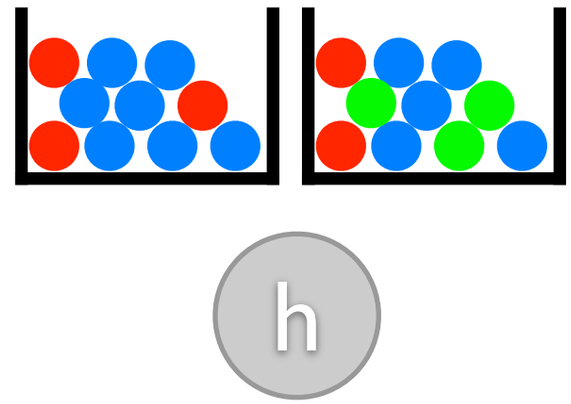
0.2 :: col(2,red); 0.3 :: col(2,green);
                   0.5 :: col(2,blue) <- true.

win :- heads, col(_,red).
```

logical rule encoding background knowledge

ProbLog by example:

A bit of gambling



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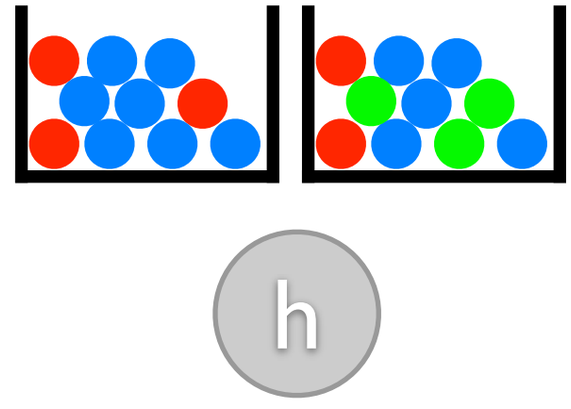
0.2 :: col(2,red); 0.3 :: col(2,green);
                   0.5 :: col(2,blue) <- true.

win :- heads, col(_,red).
win :- col(1,C), col(2,C).
```

logical rule encoding background knowledge

ProbLog by example:

A bit of gambling



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0.2 :: col(2,red); 0.3 :: col(2,green);
                   0.5 :: col(2,blue) <- true.
```

probabilistic choices

```
win :- heads, col(_,red).
win :- col(1,C), col(2,C).
```

consequences

Questions

```
0.4 :: heads.

0.3 :: col(1,red); 0.7 :: col(1,blue) <- true.
0.2 :: col(2,red); 0.3 :: col(2,green); 0.5 :: col(2,blue) <- true.

win :- heads, col(_,red).
win :- col(1,C), col(2,C).
```

marginal probability

- Probability of `win`?

conditional probability

- Probability of `win` given `col(2,green)`?

- Most probable world where `win` is true?

MPE inference

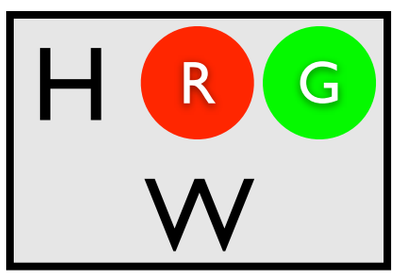
Possible Worlds

```
0.4 :: heads.

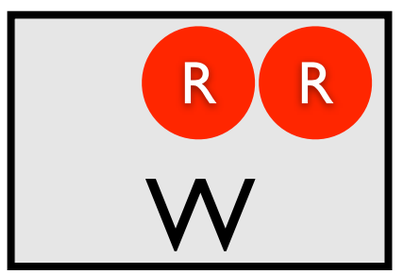
0.3 :: col(1,red); 0.7 :: col(1,blue) <- true.
0.2 :: col(2,red); 0.3 :: col(2,green); 0.5 :: col(2,blue) <- true.

win :- heads, col( ,red).
win :- col(1,C), col(2,C).
```

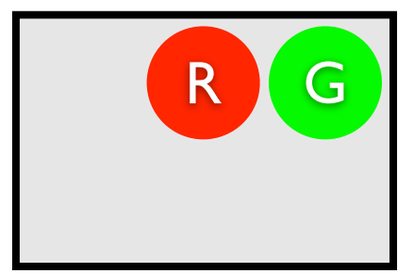
0.4 ×0.3 ×0.3



(1−0.4)×0.3 ×0.2

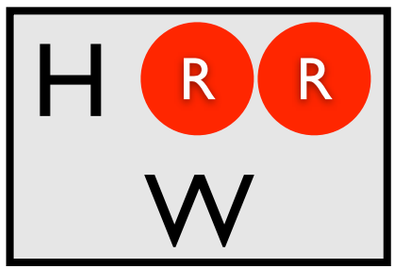


(1−0.4)×0.3 ×0.3

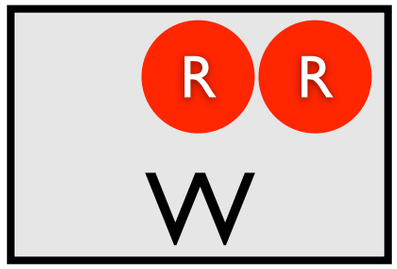


All Possible Worlds

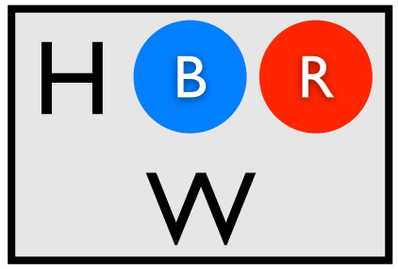
0.024



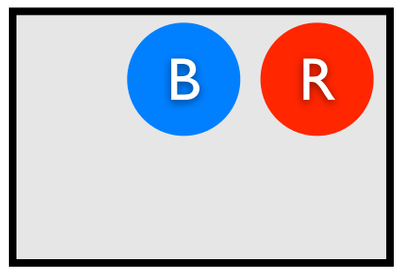
0.036



0.056



0.084



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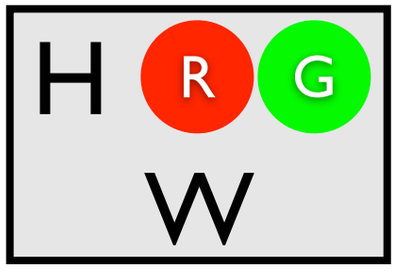

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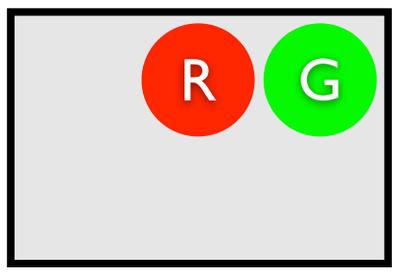

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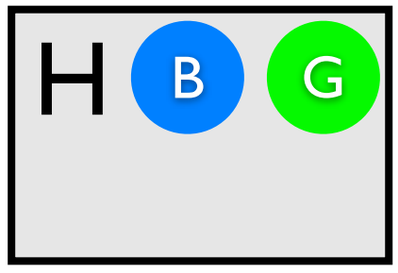
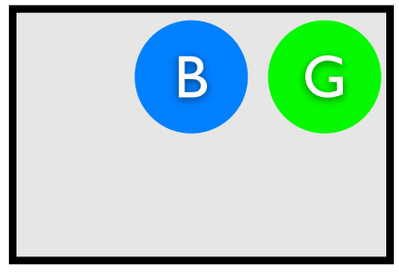
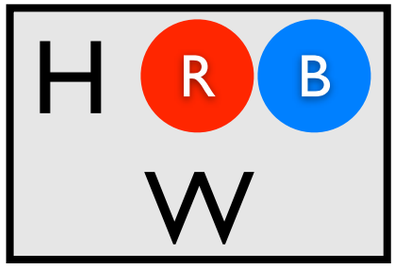


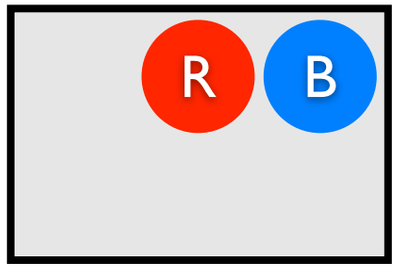
0.126



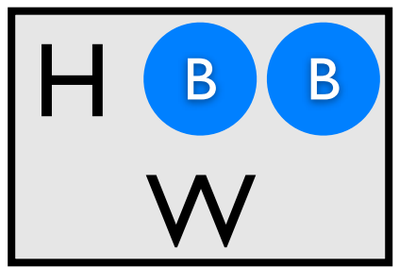
0.060



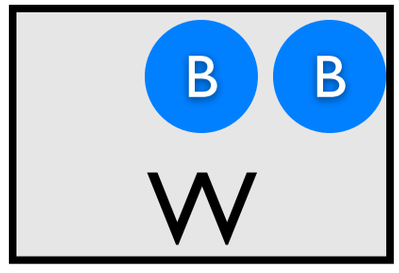
0.090



0.140



0.210



Distribution Semantics

(with probabilistic facts)

[Sato, ICLP 95]

query

sum over possible worlds where Q is true

$$P(Q) = \sum_{F \cup R \models Q} \prod_{f \in F} p(f) \prod_{f \notin F} 1 - p(f)$$

subset of probabilistic facts

Prolog rules

probability of possible world

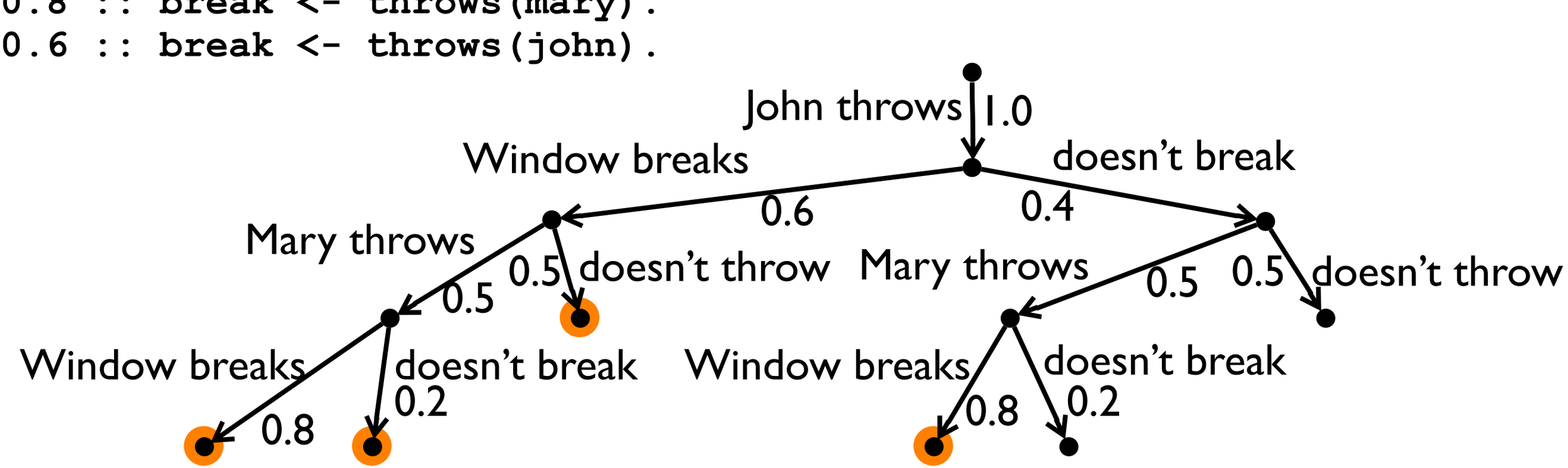
[Vennekens et al, ICLP 04]

Alternative view: CP-Logic

```
throws(john).
0.5::throws(mary).

0.8 :: break <- throws(mary).
0.6 :: break <- throws(john).
```

probabilistic causal laws



P(break)=0.6×0.5×0.8+0.6×0.5×0.2+0.6×0.5+0.4×0.5×0.8

CP-logic [Vennekens et al.]

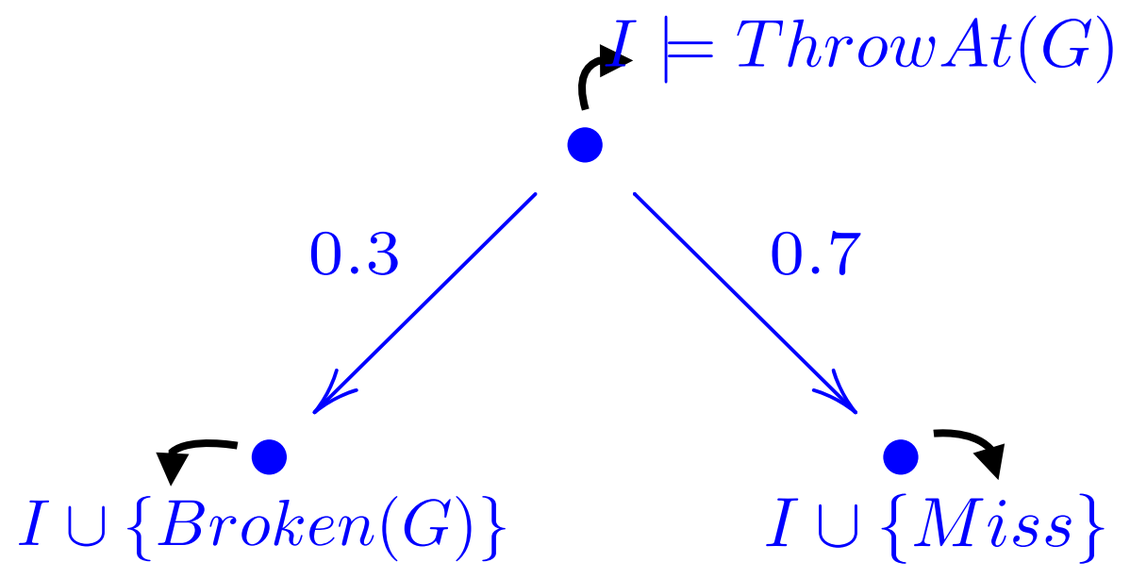
E.g., "throwing a rock at a glass breaks it with probability 0.3 and misses it with probability 0.7"

(Broken(G):0.3) ∨ (Miss 0.7) ← ThrowAt(G).

ote that the actual non-deterministic event ("rock flying at glass") is implicit

Slides CP-logic courtesy Joost Vennekens

Semantics



(Broken(G) 0.3) ∨ (Miss 0.7)
← ThrowAt(G)

Probability tree is an execution model of theory iff:

- Each tree-transition matches causal law
- The tree cannot be extended
- Each execution model defines the same probability distribution over final states

Slides CP-logic courtesy Joost Vennekens

Continuous Distributions

Distributional Clauses (DC)

- Discrete- and continuous-valued random variables

[Gutmann et al, TPLP 11; Nitti et al, IROS 13]

Distributional Clauses (DC)

- Discrete- and continuous-valued random variables

random variable with Gaussian distribution

```
length(Obj) ~ gaussian(6.0,0.45) :- type(Obj,glass).
```

[Gutmann et al, TPLP 11; Nitti et al, IROS 13]

Distributional Clauses (DC)

- Discrete- and continuous-valued random variables

```
length(Obj) ~ gaussian(6.0,0.45) :- type(Obj,glass).
stackable(OBot,OTop) :-
    ≃length(OBot) ≥ ≃length(OTop),
    ≃width(OBot) ≥ ≃width(OTop).
```

comparing values of random variables

[Gutmann et al, TPLP 11; Nitti et al, IROS 13]

Distributional Clauses (DC)

- Discrete- and continuous-valued random variables

```
length(Obj) ~ gaussian(6.0,0.45) :- type(Obj,glass).
stackable(OBot,OTop) :-
      ≃length(OBot) ≥ ≃length(OTop),
      ≃width(OBot) ≥ ≃width(OTop).
ontype(Obj,plate) ~ finite([0 : glass, 0.0024 : cup,
                            0 : pitcher, 0.8676 : plate,
                            0.0284 : bowl, 0 : serving,
                            0.1016 : none])
                    :- obj(Obj), on(Obj,O2), type(O2,plate).
```

random variable with discrete distribution

[Gutmann et al, TPLP 11; Nitti et al, IROS 13]

Distributional Clauses (DC)

- Discrete- and continuous-valued random variables

```
length(Obj) ~ gaussian(6.0,0.45) :- type(Obj,glass).
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                   :- obj(Obj), on(Obj,O2), type(O2,plate).
```

[Gutmann et al, TPLP 11; Nitti et al, IROS 13]

Distributional Clauses (DC)

- Defines a generative process (as for CP-logic)
- Tree can become infinitely wide
  - Sampling
- Well-defined under reasonable assumptions
- See Gutmann et al TPLP 11

Probabilistic Programs

- Distributional clauses / PLP similar in spirit
  - to e.g. BLOG, ... but embedded in existing logic and programming language
  - to e.g. Church but use of logic instead of functional programming ...
    - natural possible world semantics and link with prob. databases.
    - somewhat harder to do meta-programming

Markov Logic

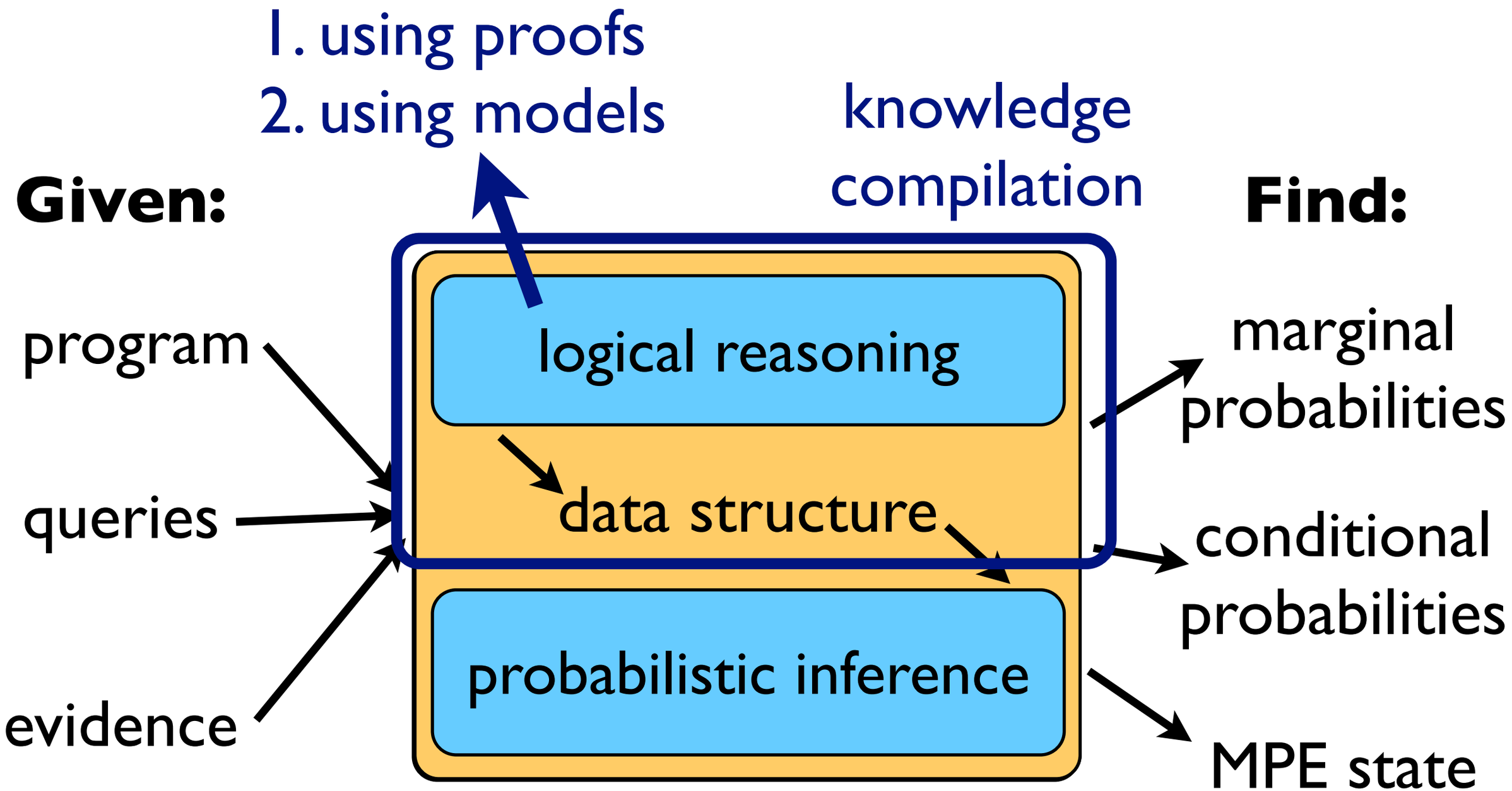
Key differences

- programming language
- Dist. Sem. uses least-fix point semantics
  - can express transitive closure of relation
  - this cannot be expressed in FOL (and Markov Logic), requires second order logic
  - p(X,Y) :- p(X,Z), p(Z,Y).

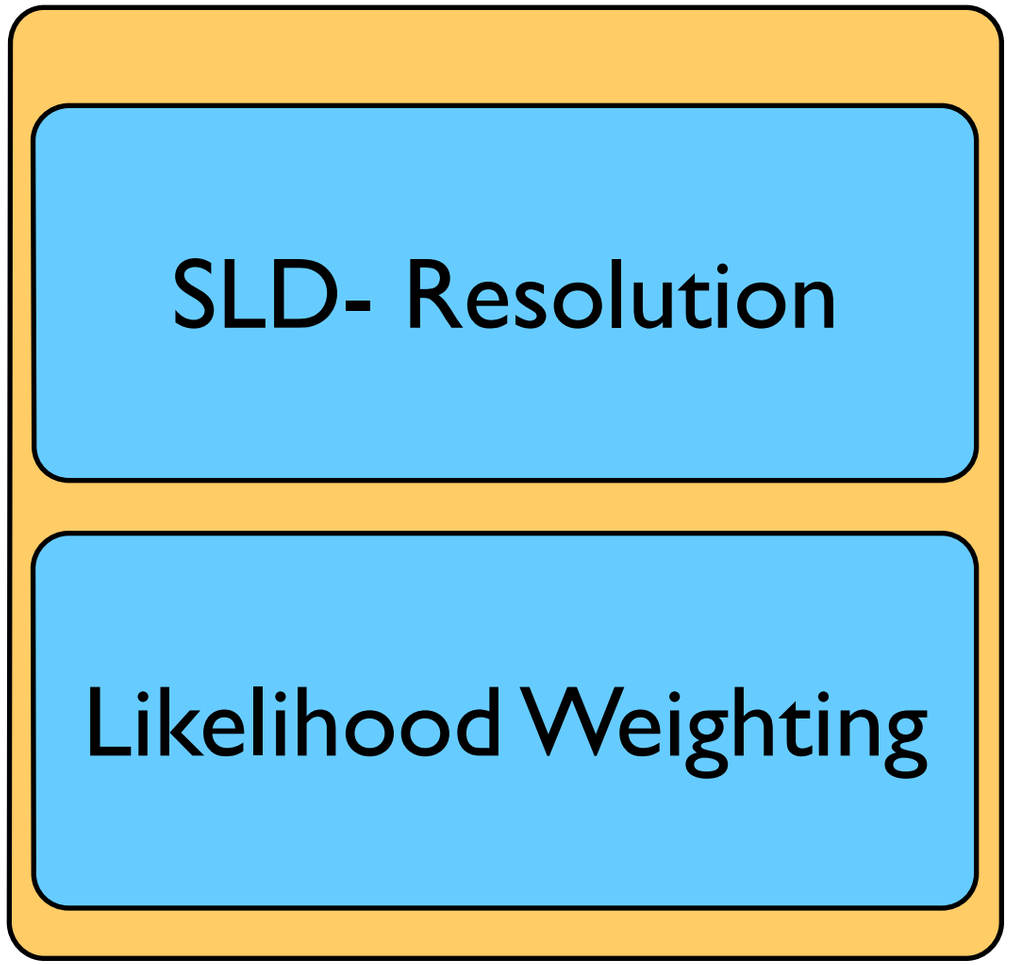
Inference in PLP

- As in Prolog and logic programming
  - proof-based
- As in Answer Set Programming
  - model based
- As in Probabilistic Programming
  - sampling

Inference


1. using proofs
2. using models
knowledge compilation
Given:
Find:
program
queries
evidence
logical reasoning
data structure
probabilistic inference
marginal probabilities
conditional probabilities
MPE state

Inference for DC




```
n ~ uniform([1, 2, 3, 4, 5, 6, 7, 8, 9, 10]).
color(X) ~ uniform([grey, blue, black]) ← material(X) ~= metal.
color(X) ~ uniform([black, brown]) ← material(X) ~=wood.
material(X)~finite([0.3:wood,0.7:metal])←n~=N,between(1,N,X).
drawn(Y) ~ uniform(L) ← n ~= N, findall(X, between(1, N, X), L).
size(X) ~ beta(2, 3) ← material(X) ~= metal.
size(X) ~ beta(4, 2) ← material(X) ~= wood.
```

LW for DC

Given a goal G and the global variables $w_q^{(i)}, iq, x^{P(i)}$, applying a rule produces a new goal G' and modifies the global variables:

1. G' is the new goal obtained from G using a kind of SLD-resolution step;
2. if a new variable r is sampled with value v,
   - set $w_q^{(i)} \leftarrow w_q^{(i)} \frac{p(r=v|x^{P(i)})}{g(r=v|x^{P(i)})}$ (based on LW) and
   - $x^{P(i)} \leftarrow x^{P(i)} \cup \{r = v\}$.

   In addition, if $r = Val \in iq$ with r grounded, then:
   - $iq \leftarrow iq\theta$ with $\theta = \{Val = v\}$.
3. if a new atom a is proved set $x^{P(i)} \leftarrow x^{P(i)} \cup \{a\}$.

$1: (\texttt{color}(2) \sim= \texttt{black}); w_q^{(i)} = 1; x^{P(i)} = \emptyset$

↓ 2b on (7) :

$2: (\texttt{material}(2) \sim= \texttt{metal}, \texttt{sample}(\texttt{color}(2), \mathcal{D}_{\texttt{color}(2)}), \texttt{color}(2) \sim= \texttt{black}); w_q^{(i)} = 1; x^{P(i)} = \emptyset$

↓ 2b on (9) :

$3: (\texttt{n} \sim= \texttt{N}, \texttt{between}(1, \texttt{N}, 2), \texttt{sample}(\texttt{material}(2), \mathcal{D}_{\texttt{material}(2)}), \texttt{material}(2) \sim= \texttt{metal},$
$\texttt{sample}(\texttt{color}(2), \mathcal{D}_{\texttt{color}(2)}), \texttt{color}(2) \sim= \texttt{black}); w_q^{(i)} = 1;\ x^{P(i)} = \emptyset$

↓ 2b on (6) :

$4: (\texttt{sample}(\texttt{n}, \mathcal{D}_{\texttt{n}}), \texttt{n} \sim= \texttt{N}, \texttt{between}(1, \simeq(\texttt{n}), 2), \texttt{sample}(\texttt{material}(2), \mathcal{D}_{\texttt{material}(2)}),$
$\texttt{material}(2) \sim= \texttt{metal}, \texttt{sample}(\texttt{color}(2), \mathcal{D}_{\texttt{color}(2)}), \texttt{color}(2) \sim= \texttt{black}); w_q^{(i)} = 1; x^{P(i)} = \emptyset$

↓ 3b :

$5: (\texttt{n} \sim= 3, \texttt{between}(1, 3, 2), \texttt{sample}(\texttt{material}(2), \mathcal{D}_{\texttt{material}(2)}), \texttt{material}(2) \sim= \texttt{metal},$
$\texttt{sample}(\texttt{color}(2), \mathcal{D}_{\texttt{color}(2)}), \texttt{color}(2) \sim= \texttt{black}); w_q^{(i)} = 1;\ x^{P(i)} = \{\texttt{n} = 3\}$

↓ 2a followed by 1a

$6: (\texttt{sample}(\texttt{material}(2), \mathcal{D}_{\texttt{material}(2)}), \texttt{material}(2) \sim= \texttt{metal}, \texttt{sample}(\texttt{color}(2),$
$\texttt{color}(2) \sim= \texttt{black}); w_q^{(i)} = 1;\ x^{P(i)} = \{\texttt{n} = 3\}$

↓ 3b :

$7: (\texttt{material}(2) \sim= \texttt{metal}, \texttt{sample}(\texttt{color}(2), \mathcal{D}_{\texttt{color}(2)}), \texttt{color}(2) \sim= \texttt{black})$
$w_q^{(i)} = 1;\ x^{P(i)} = \{\texttt{n} = 3, \texttt{material}(2) = \texttt{wood}\}$

fail, backtracking to 1

$$\mathtt{n} \sim \mathtt{uniform}([1,2,3,4,5,6,7,8,9,10]). \quad (6)$$

$$\mathtt{color}(\mathtt{X}) \sim \mathtt{uniform}([\mathtt{grey},\mathtt{blue},\mathtt{black}]) \leftarrow \mathtt{material}(\mathtt{X}) \sim= \mathtt{metal}. \quad (7)$$

$$\mathtt{color}(\mathtt{X}) \sim \mathtt{uniform}([\mathtt{black},\mathtt{brown}]) \leftarrow \mathtt{material}(\mathtt{X}) \sim= \mathtt{wood}. \quad (8)$$

$$\mathtt{material}(\mathtt{X}) \sim \mathtt{finite}([0.3{:}\mathtt{wood}, 0.7{:}\mathtt{metal}]) \leftarrow \mathtt{n} \sim= \mathtt{N}, \mathtt{between}(1,\mathtt{N},\mathtt{X}). \quad (9)$$

$$\mathtt{drawn}(\mathtt{Y}) \sim \mathtt{uniform}(\mathtt{L}) \leftarrow \mathtt{n} \sim= \mathtt{N}, \mathtt{findall}(\mathtt{X}, \mathtt{between}(1,\mathtt{N},\mathtt{X}), \mathtt{L}). \quad (10)$$

$$\mathtt{size}(\mathtt{X}) \sim \mathtt{beta}(2,3) \leftarrow \mathtt{material}(\mathtt{X}) \sim= \mathtt{metal}. \quad (11)$$

$$\mathtt{size}(\mathtt{X}) \sim \mathtt{beta}(4,2) \leftarrow \mathtt{material}(\mathtt{X}) \sim= \mathtt{wood}. \quad (12)$$

$1: (\mathtt{color}(2) \sim= \mathtt{black}); w_q^{(i)} = 1; x^{P(i)} = \emptyset$

↓ 2b on (8) :

$9: (\mathtt{material}(2) \sim= \mathtt{wood}, \mathtt{sample}(\mathtt{color}(2), \mathcal{D}_{\mathtt{color}(2)}), \mathtt{color}(2) \sim= \mathtt{black})$

$w_q^{(i)} = 1;\ x^{P(i)} = \{\mathtt{n} = 3, \mathtt{material}(2) = \mathtt{wood}\}$

↓ 2a :

$10: (\mathtt{sample}(\mathtt{color}(2), \mathcal{D}_{\mathtt{color}(2)}), \mathtt{color}(2) \sim= \mathtt{black}); w = 1; x^{P(i)} = \{\mathtt{n} = 3, \mathtt{material}(2) = \mathtt{wood}\}$

↓ 3a :

$11: (\mathtt{color}(2) \sim= \mathtt{black}); w_q^{(i)} = 1/3;\ x^{P(i)} = \{\mathtt{n} = 3, \mathtt{material}(2) = \mathtt{wood}, \mathtt{color}(2) = \mathtt{black}\}$

↓ 1a :

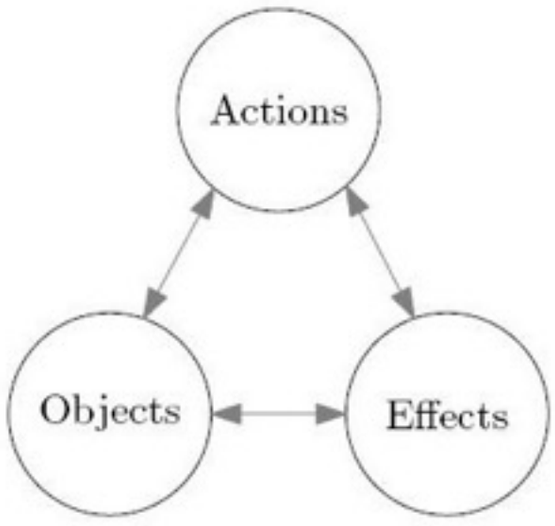
$12: \square; w_q^{(i)} = 1/3;\ x^{P(i)} = \{\mathtt{n} = 3, \mathtt{material}(2) = \mathtt{wood}, \mathtt{color}(2) = \mathtt{black}\}$

can cope with evidence like color(1) = color(2)
and size(1) = 0.356, size(1)=size(2), …
outperforms BLOG … unification + LW

Affordances with DCs

Affordances

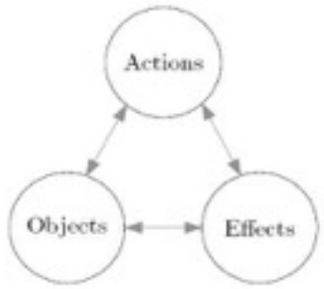
- Model captures action opportunities
  - What can one do with an object?
- Three main aspects:
  - Object (properties):
    - Measured from perceptual devices
    - shape, size, …
  - Action:
    - Applied physical manipulation
    - Tap, Push, Grab
  - Effects:
    - Measurable features after action
    - displacement, orientation, ...



Inputs	Outputs	Function
(O, A)	E	Effect prediction
(O, E)	A	Action recognition/planning
(A, E)	O	Object recognition/selection

Learning relational affordances

Learn probabilistic model



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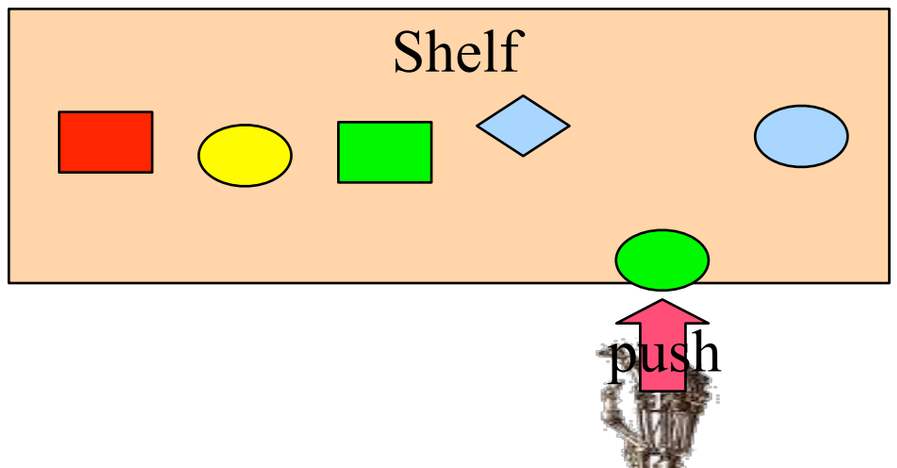
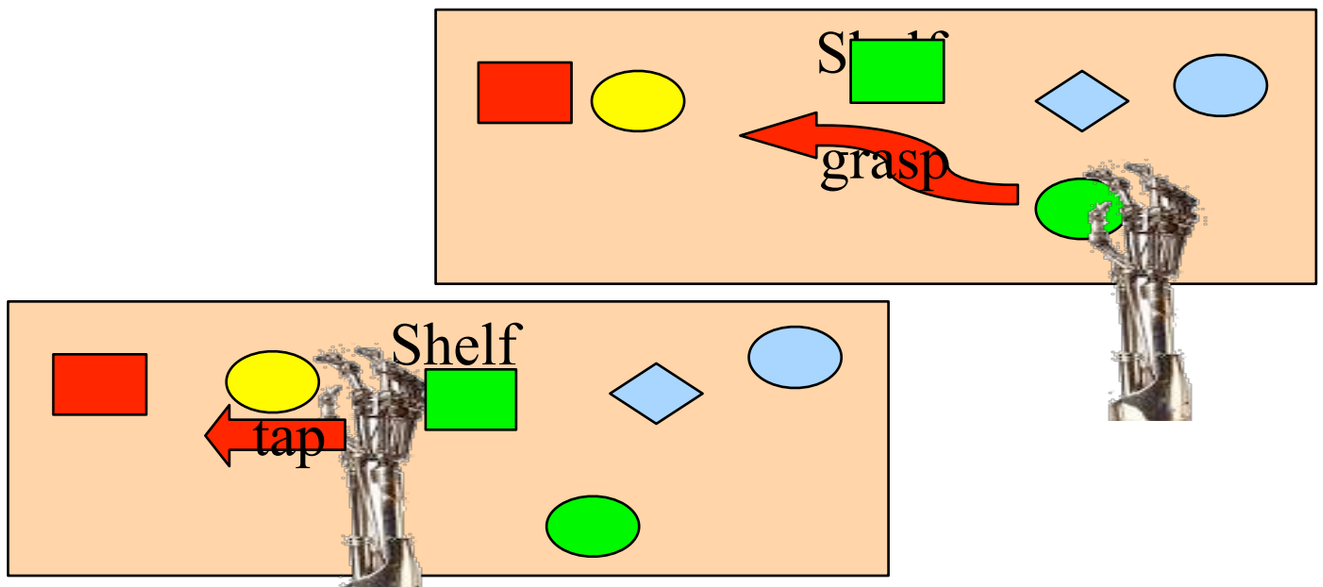
Learning relational affordances between two objects (learnt by experience)

From two object interactions

Generalize to N

***Moldovan** et al. ICRA 12, 13, 14, PhD 15*





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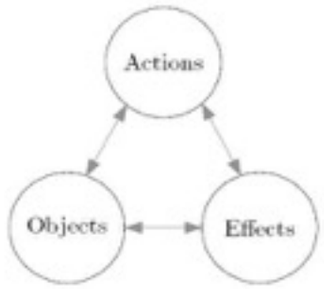
Learn probabilistic model



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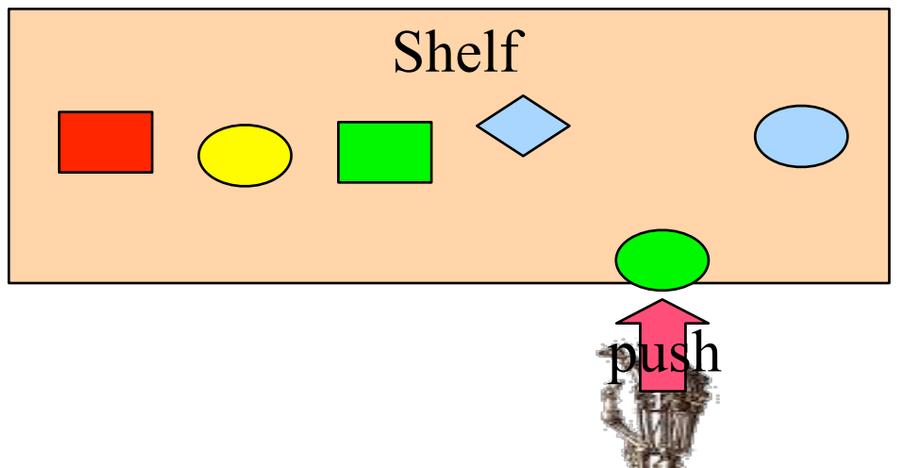
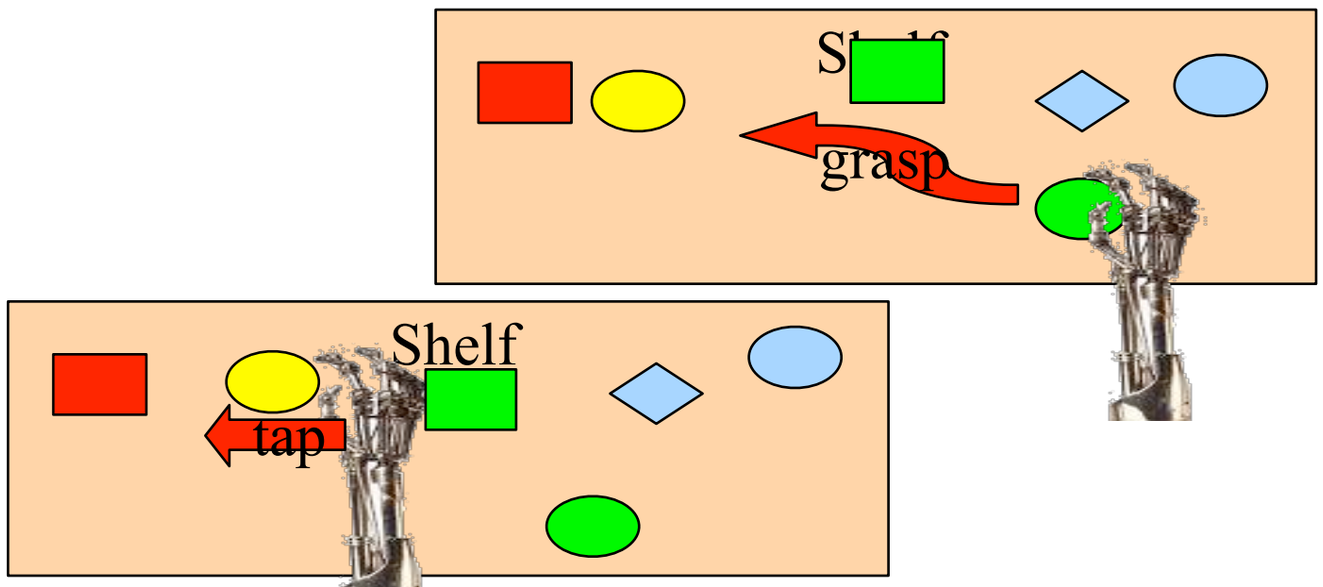




Learning relational affordances between two objects (learnt by experience)

Right Arm

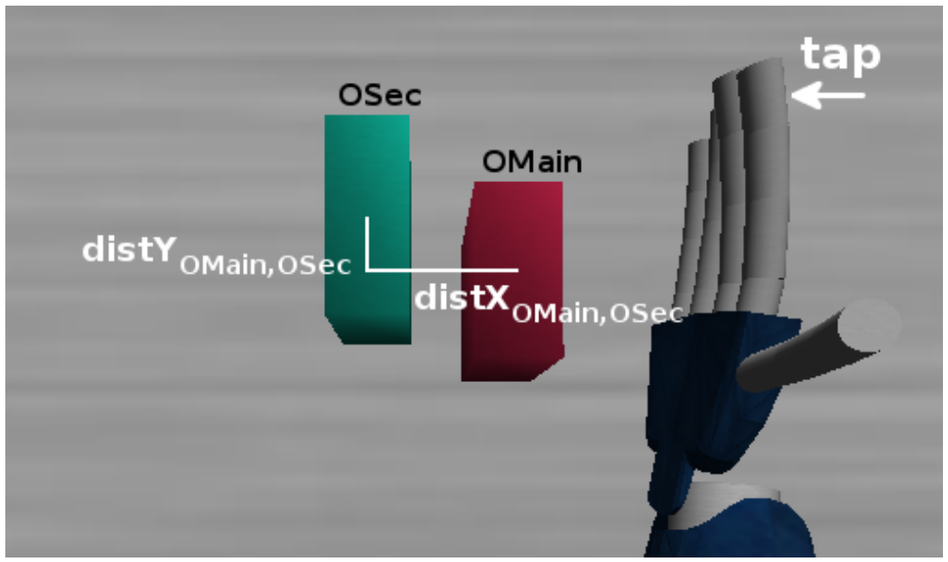
Examples

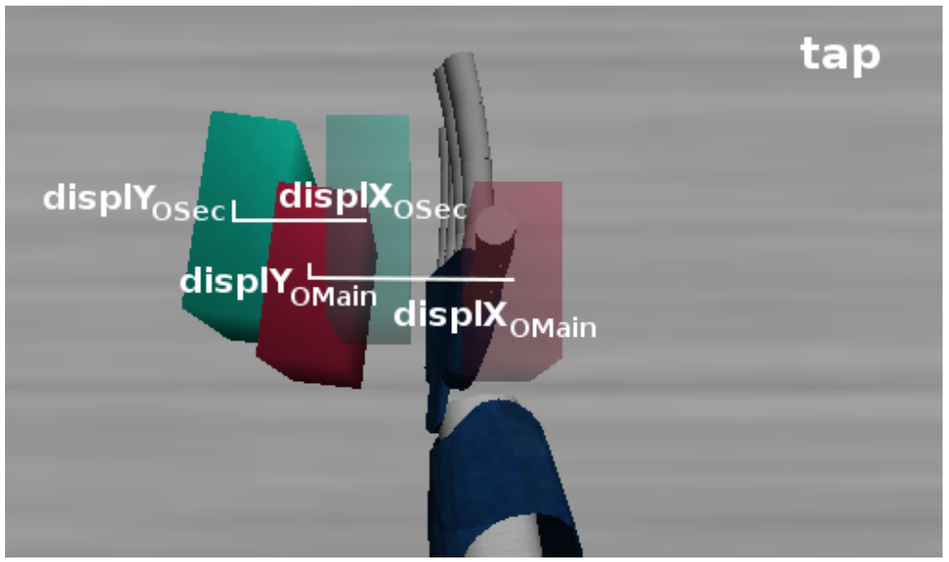
Learning relational affordances between two objects (learnt by experience)

Right Arm

Examples

What is an affordance ?





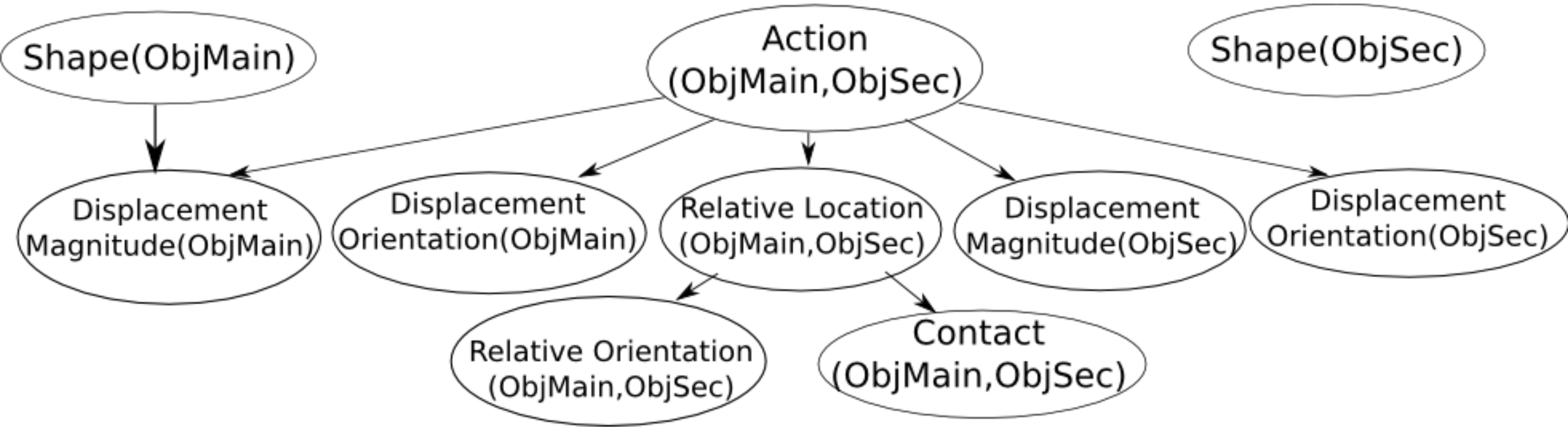
Clip 8: Relational O before (l), and E after the action execution (r).

Table 1: Example collected O, A, E data for action in Figure 8

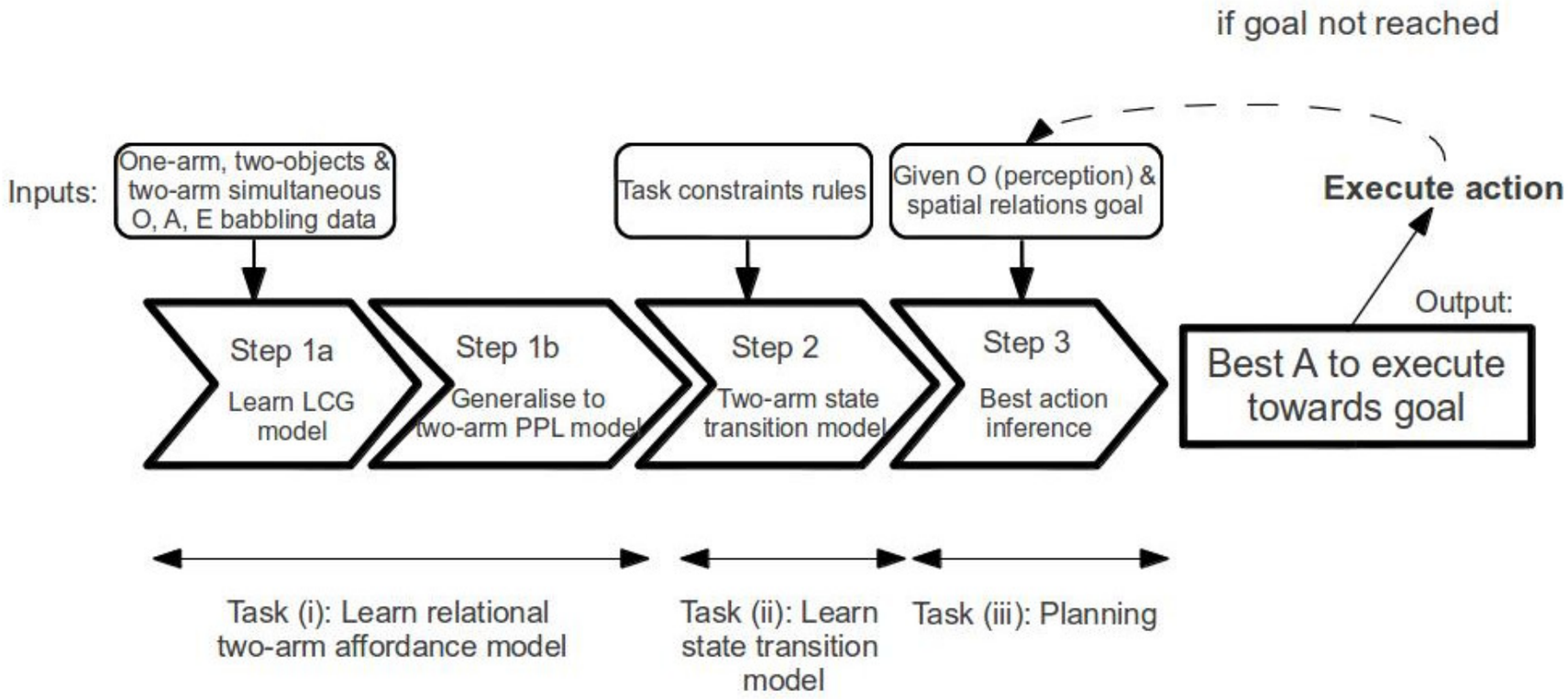
Object Properties	**Action**	**Effects**
$shape_{O_{Main}} : sprism$ $shape_{O_{Sec}} : sprism$ $distX_{O_{Main},O_{Sec}} : 6.94cm$ $distY_{O_{Main},O_{Sec}} : 1.90cm$	$tap(10)$	$displX_{O_{Main}} : 10.33cm$ $displY_{O_{Main}} : -0.68cm$ $displX_{O_{Sec}} : 7.43cm$ $displY_{O_{Sec}} : -1.31cm$

- Formalism — related to STRIPS but models delta
- but also joint probability model over A, E, O

Bayesian Network



Learning relational affordances



Clip 4: Pipeline for table-top two-arm object manipulation.

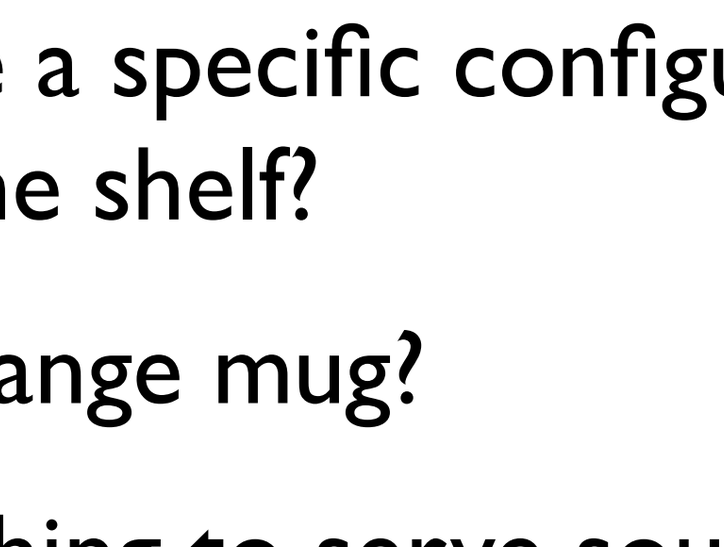
- 1a) learn a Linear Continuous Gaussian (LCG) Bayesian Network (BN) from single arm and simultaneous two-arm exploratory data,
- 1b) from the LCG model, build the two-arm continuous domain relational affordance model in a PPL,
- 2) build a state transition model from the relational affordance model, and
- 3) infer best action to execute to reach goal (step repeated until goal reached).

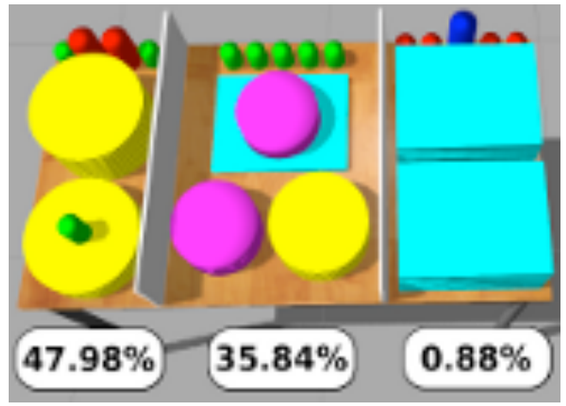
Remaining challenge

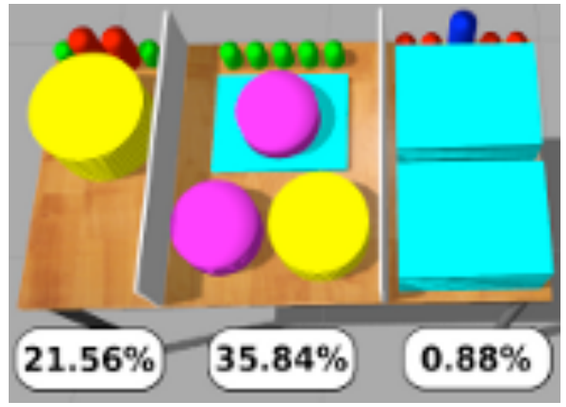
- Learn DC model directly
- Work on planning with DC (Nitti et al., ECML, EWRL 15)

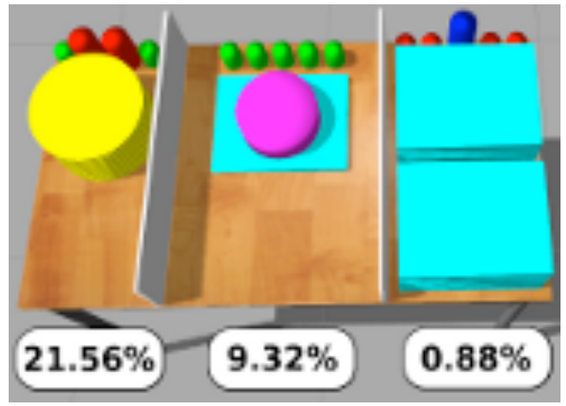
Occluded Object Search

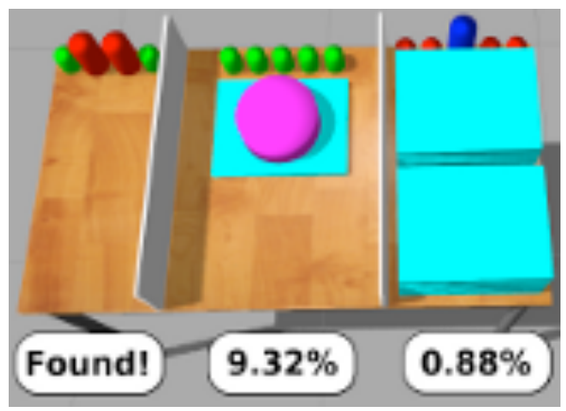
- How to achieve a specific configuration of objects on the shelf?
- Where's the orange mug?
- Where's something to serve soup in?
- Models of objects and their spatial arrangement







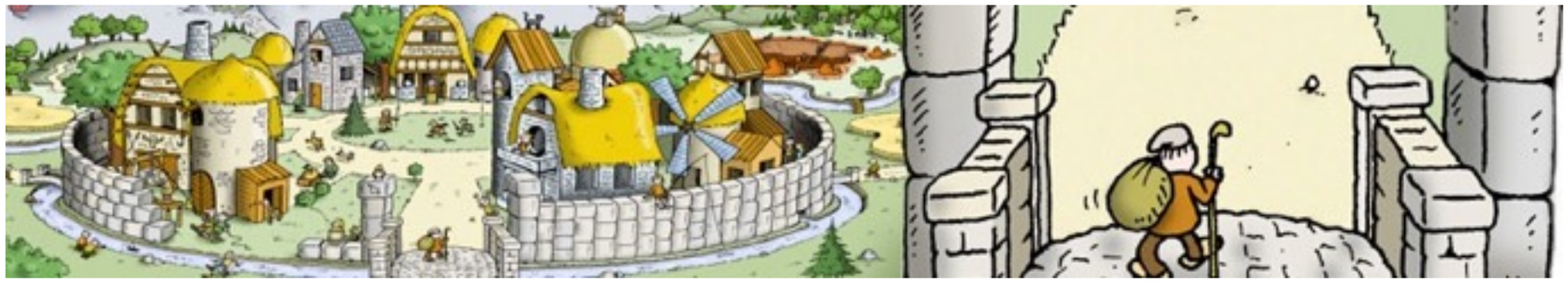




[Moldovan *et al. 14*]

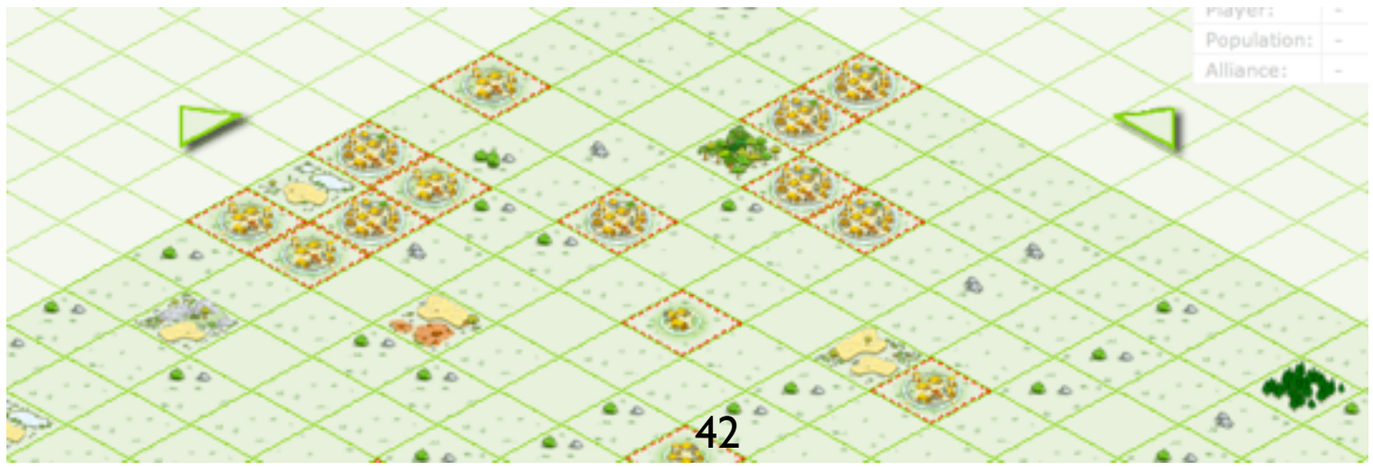
Dynamics

Dynamics: Evolving Networks



- *Travian*: A massively multiplayer real-time strategy game
- Commercial game run by TravianGames GmbH
- ~3.000.000 players spread over different "worlds"
- ~25.000 players in one world

[Thon et al. MLJ 11]



World Dynamics

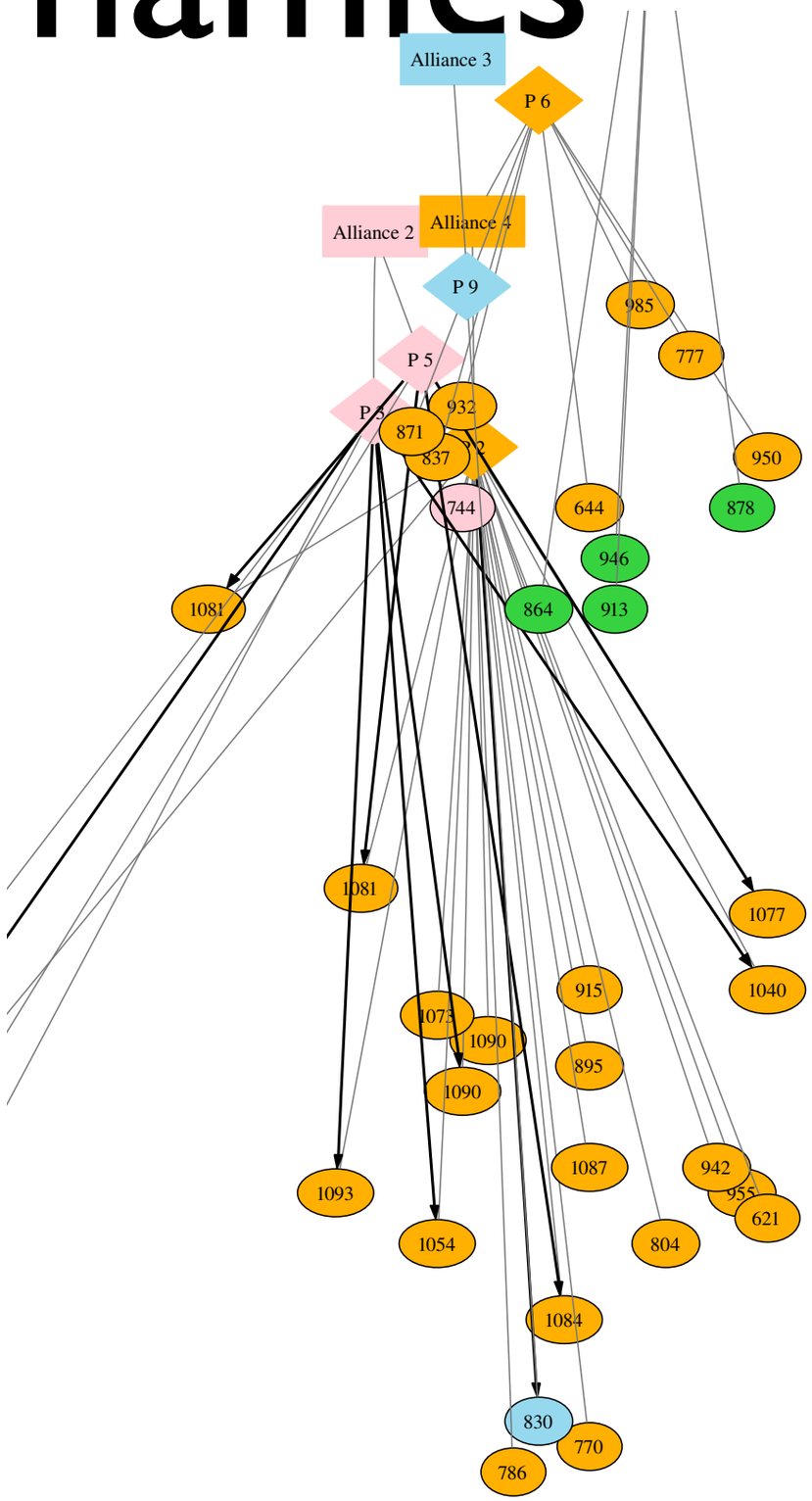
Fragment of world with

~10 alliances
~200 players
~600 cities

alliances color-coded

Can we build a model
of this world ?
Can we use it for playing
better ?

[Thon, Landwehr, De Raedt, ECML08]



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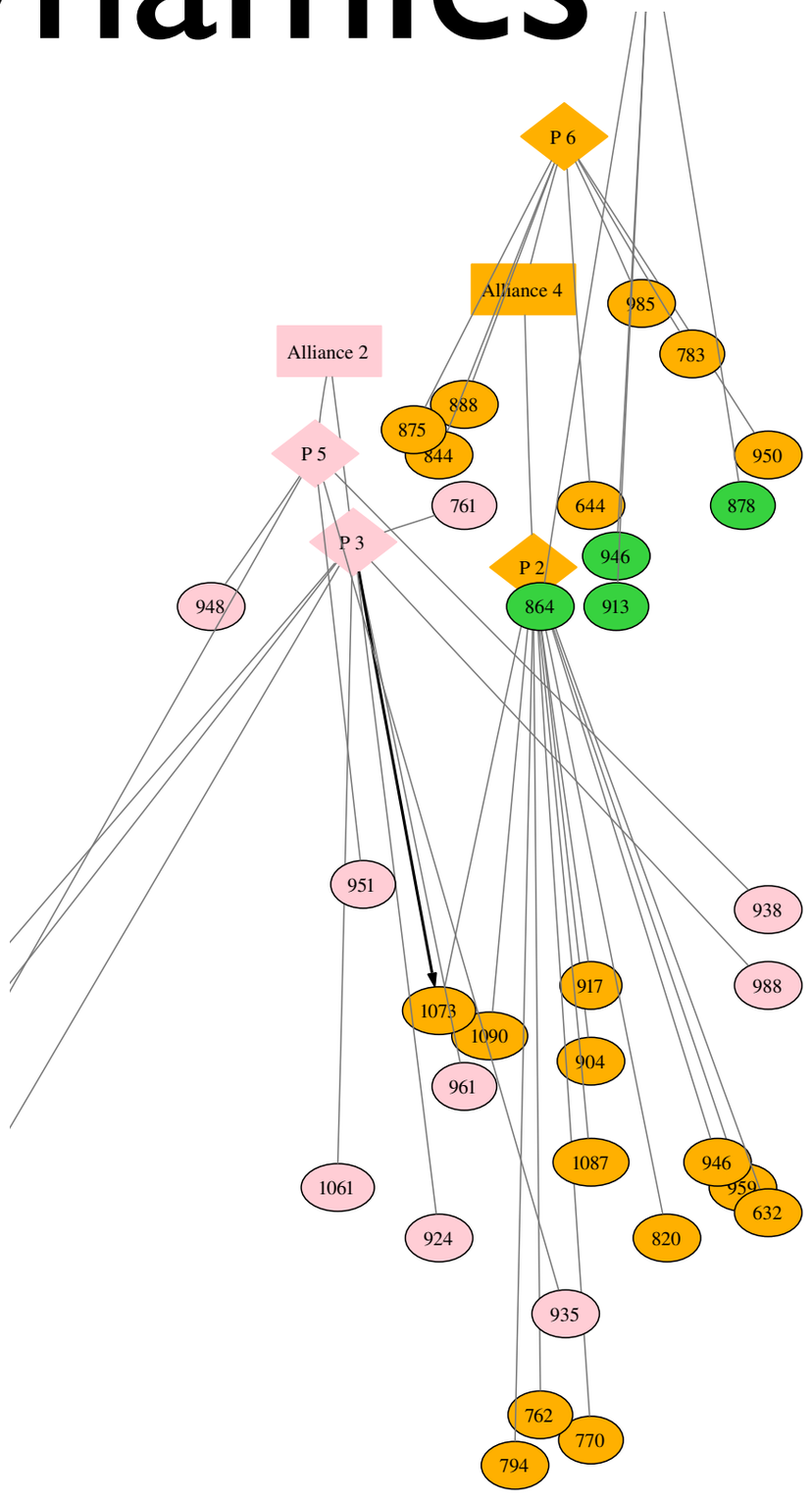

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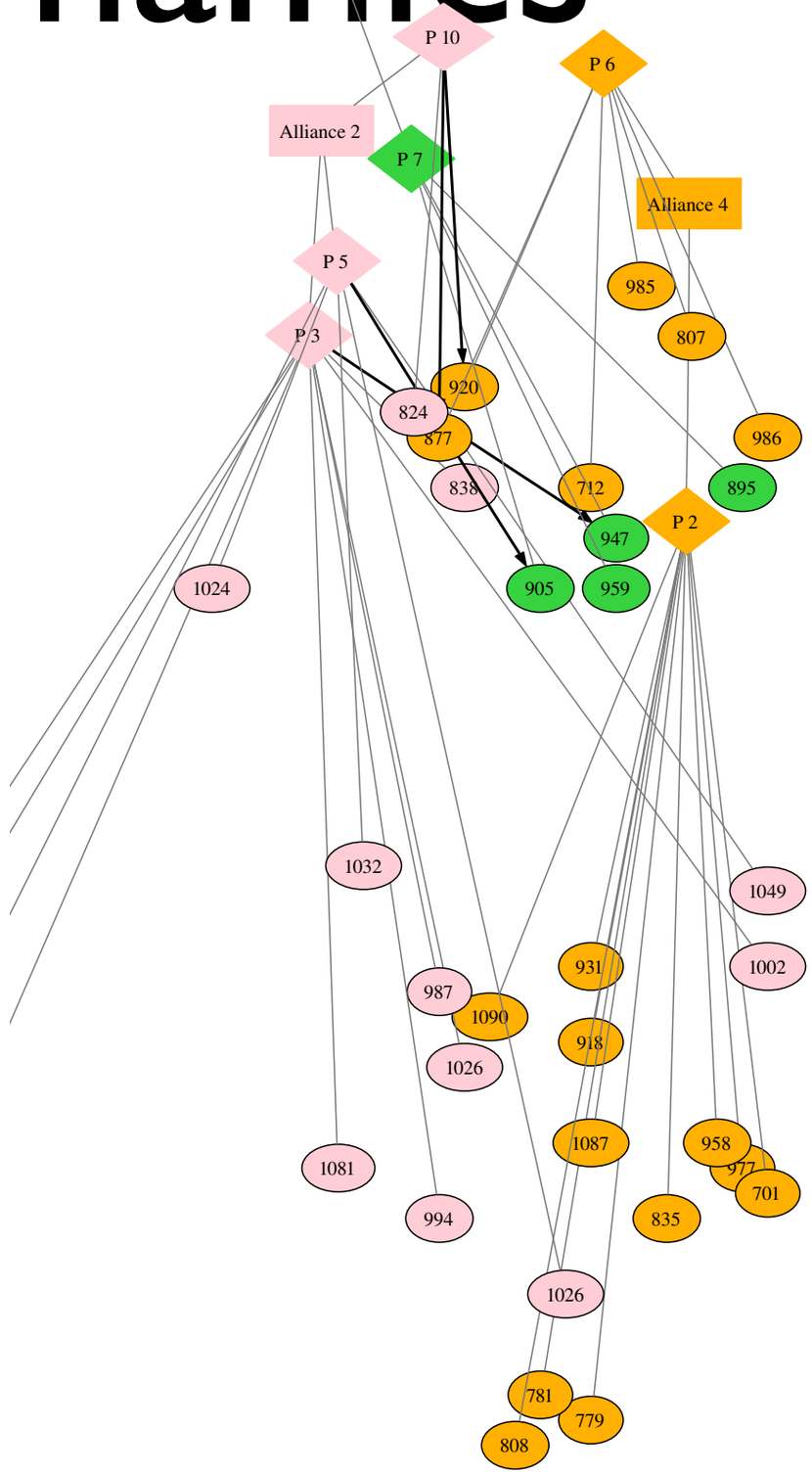

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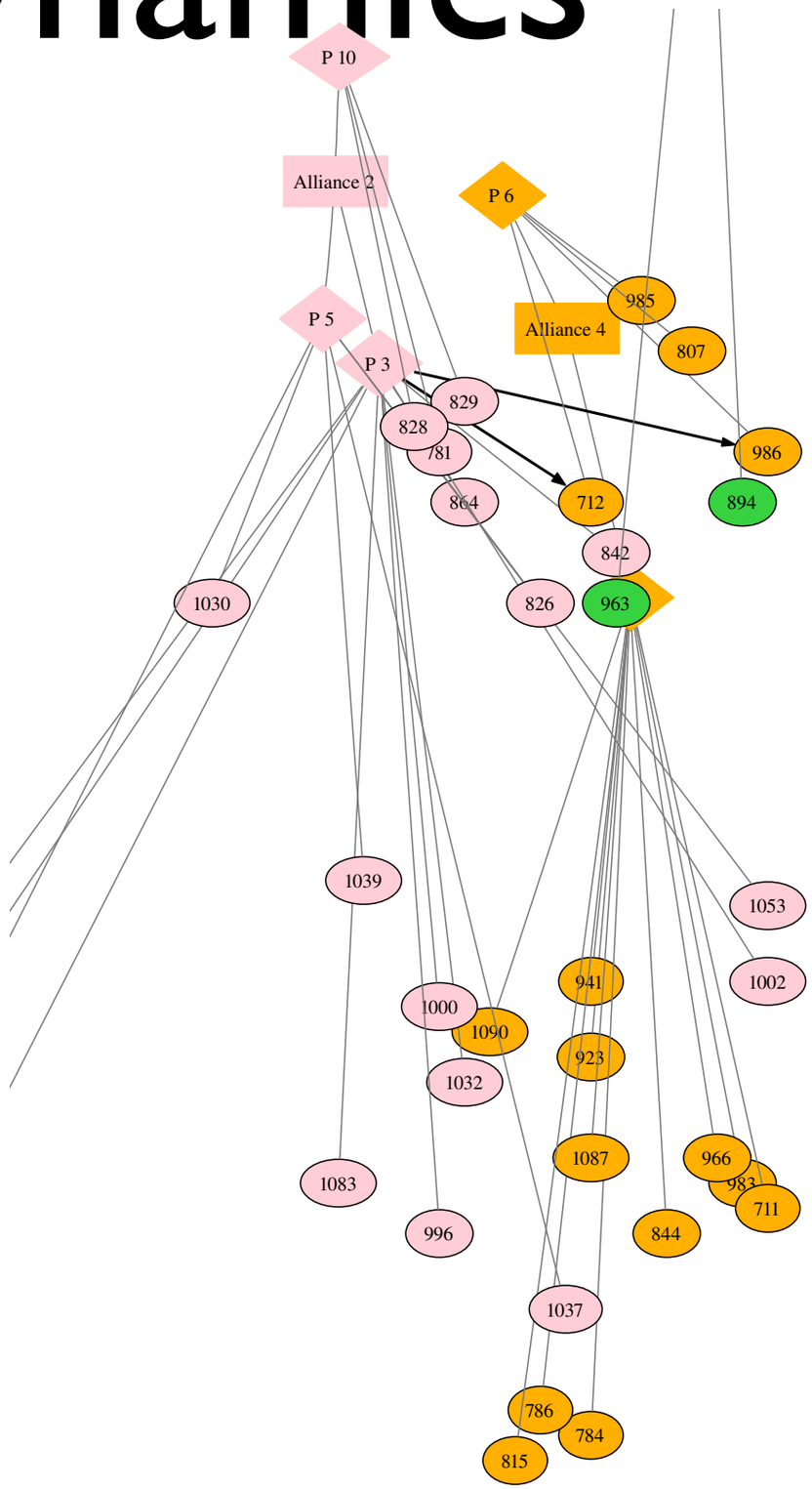

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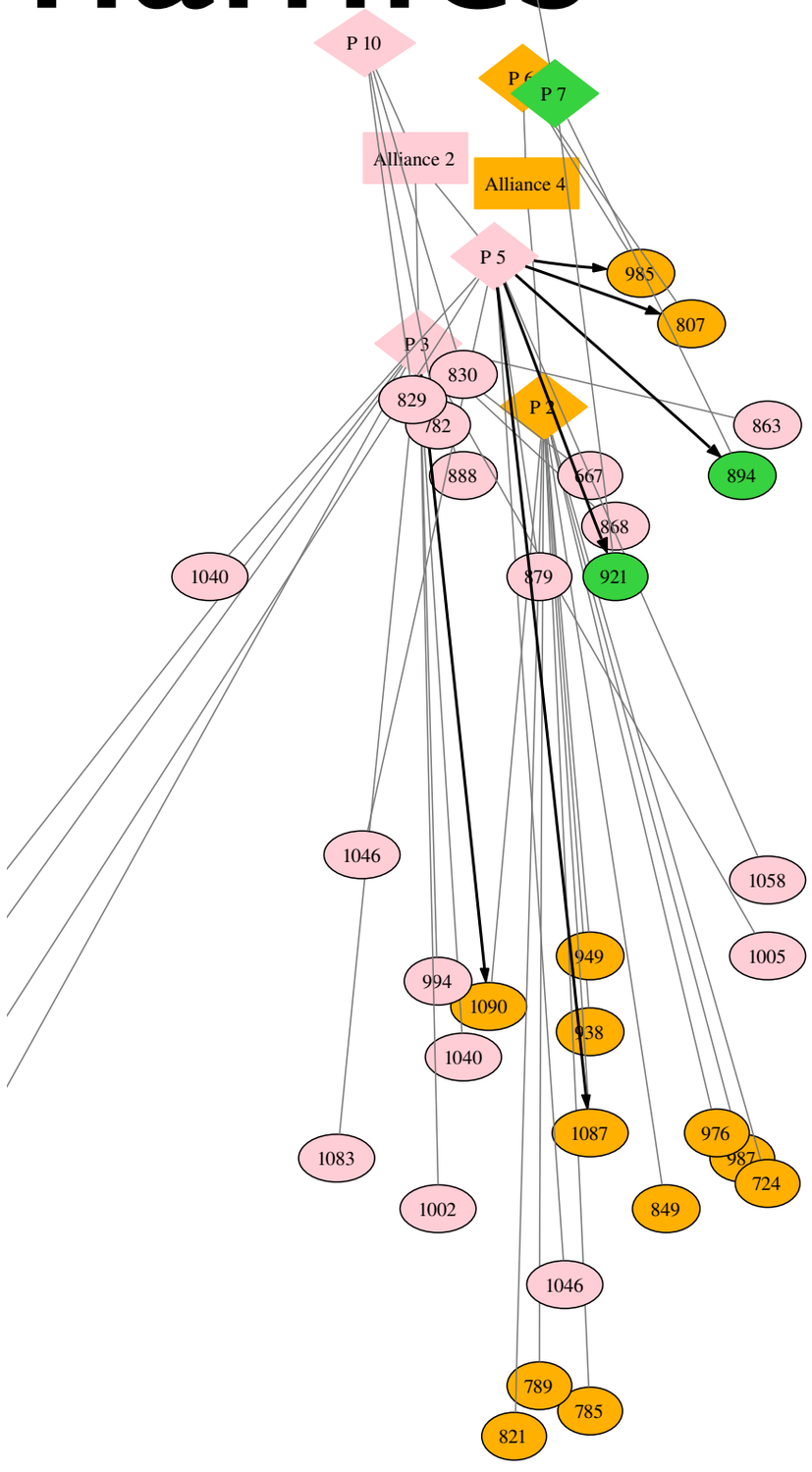

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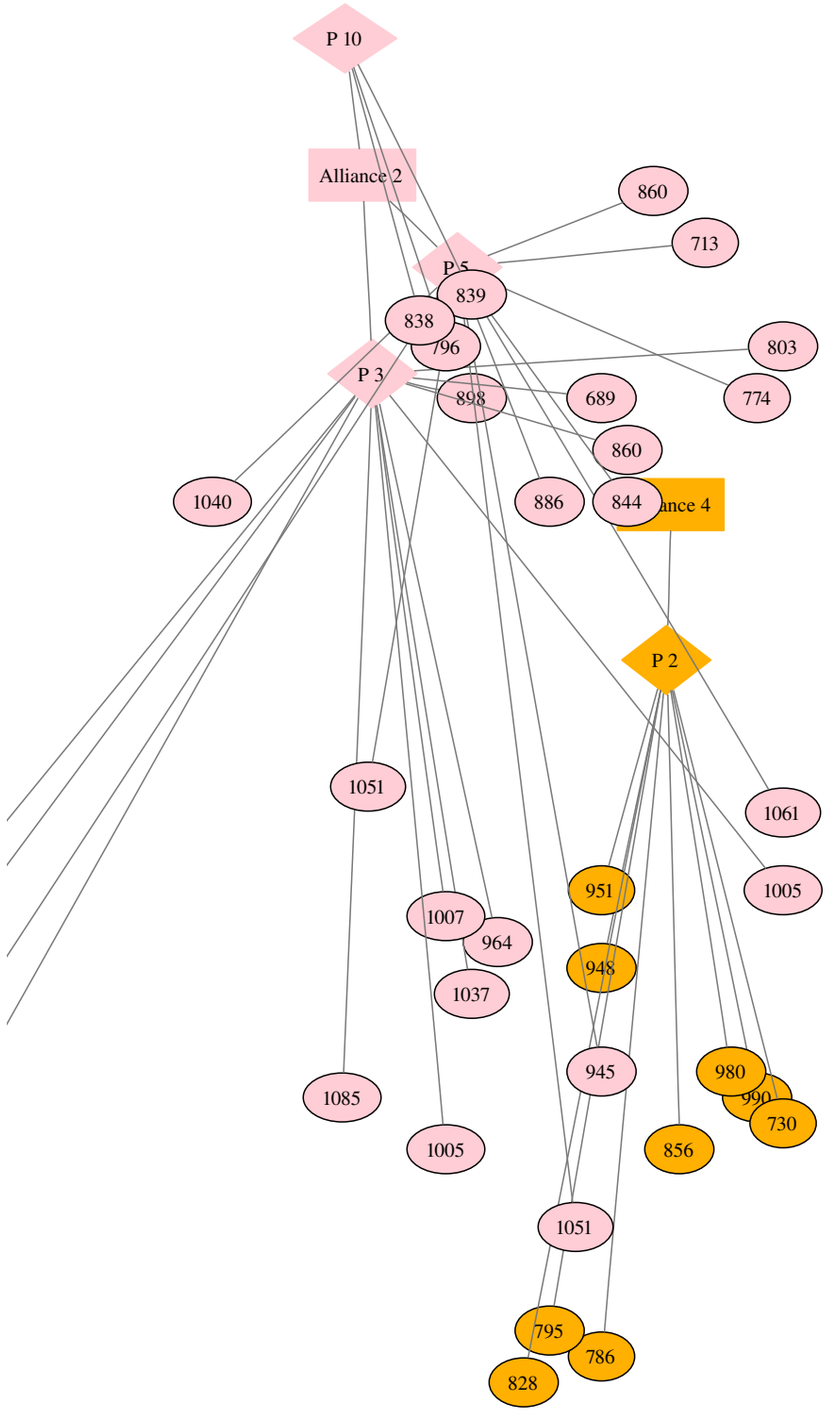
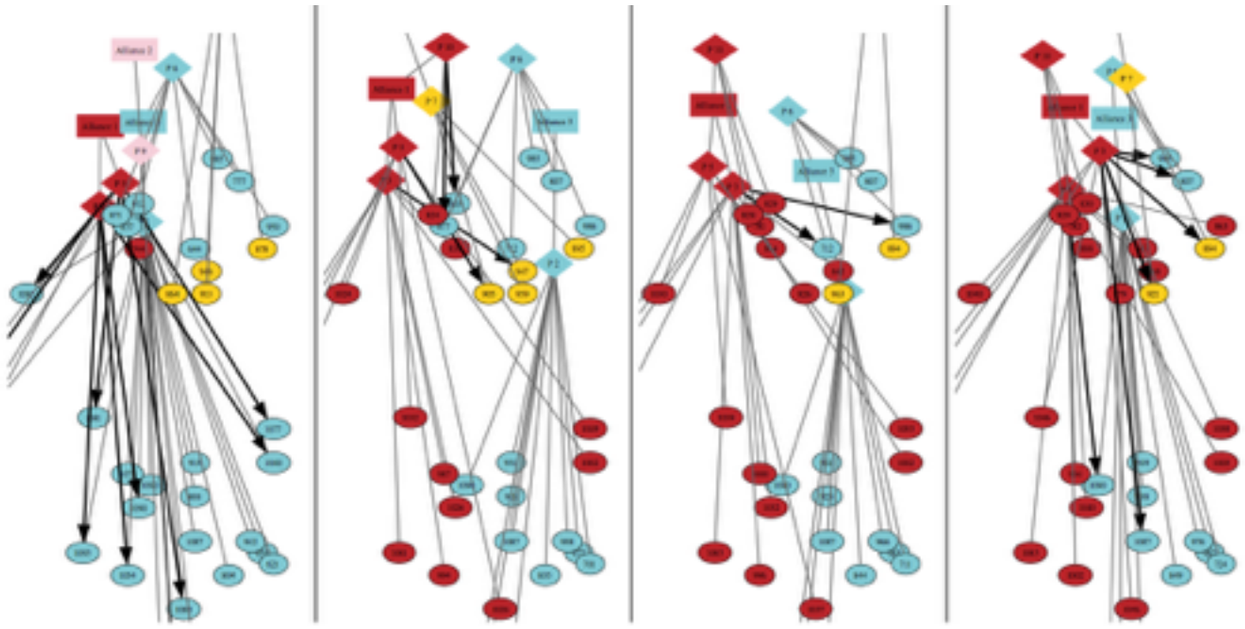


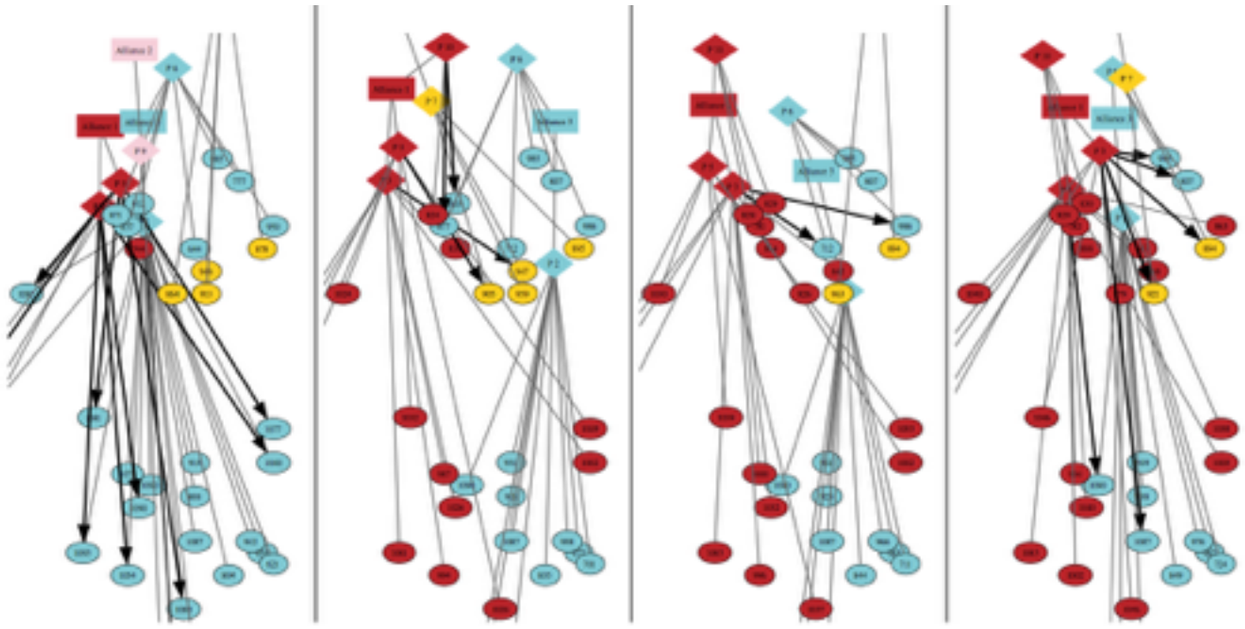
Causal Probabilistic Time-Logic (CPT-L)



how does the world change over time?

[Thon et al, MLJ 11]

Causal Probabilistic Time-Logic (CPT-L)



how does the world change over time?

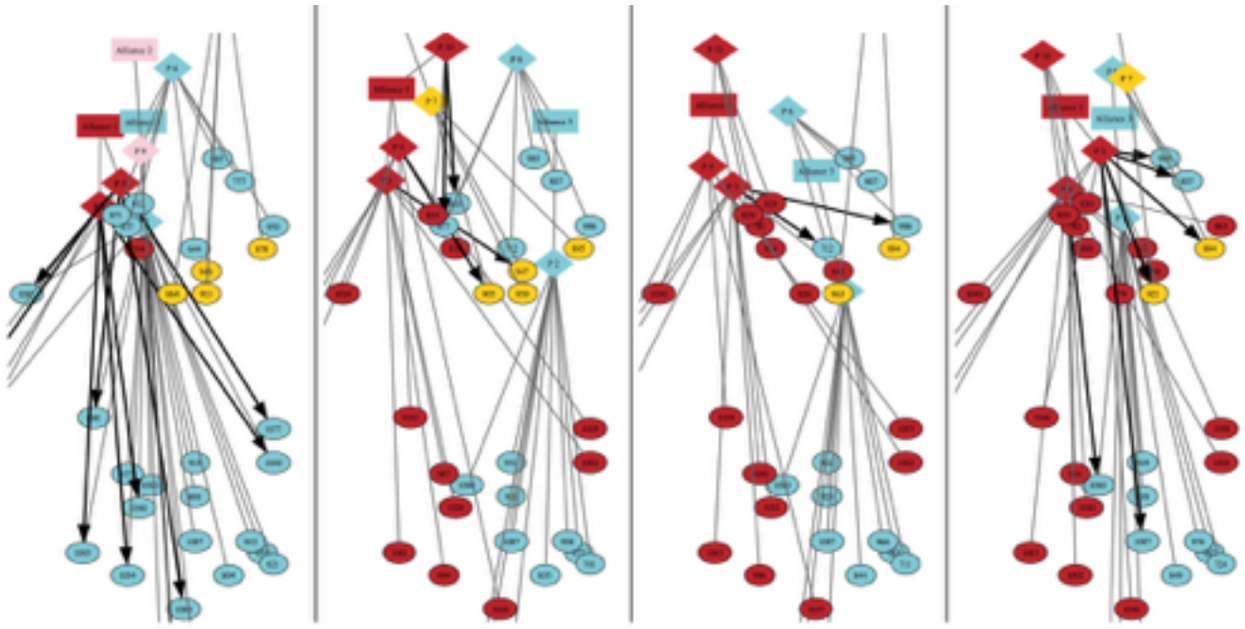
```
0.4::conquest(Attacker,C); 0.6::nil <-
```

```
city(C,Owner),city(C2,Attacker),close(C,C2).
```

if **cause** holds at time T

[Thon et al, MLJ 11]

Causal Probabilistic Time-Logic (CPT-L)



how does the world change over time?

one of the **effects** holds at time T+1

```
0.4::conquest(Attacker,C); 0.6::nil <-
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```

if **cause** holds at time T

[Thon et al, MLJ 11]

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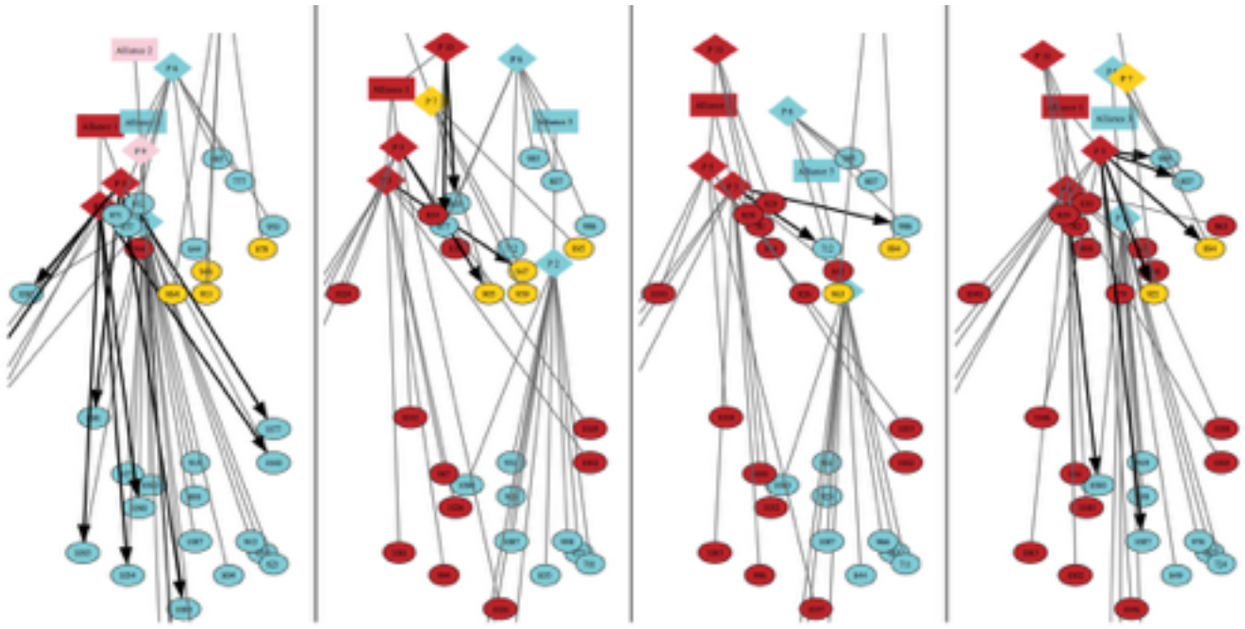

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if **cause** holds at time T

[Thon et al, MLJ 11]

Limitations CPT-L

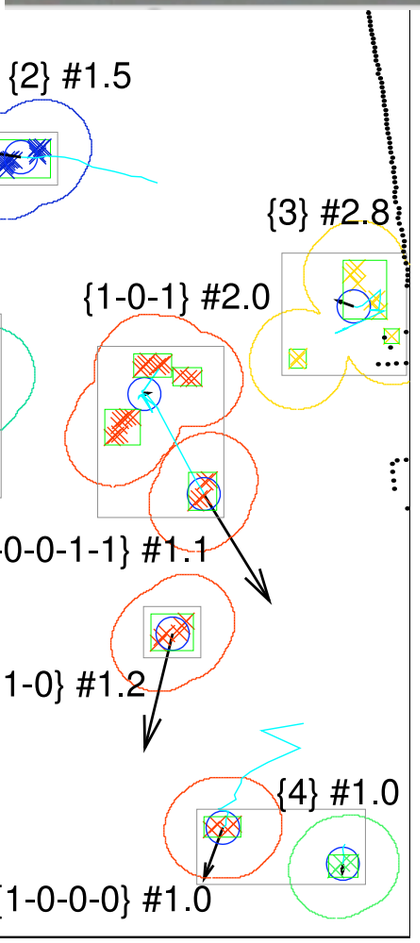
Inference slow / scalability

- uses knowledge compilation method
- compile formula for $P(I_{t+1}|I_{[0,t]})$
- exponential in number of time steps

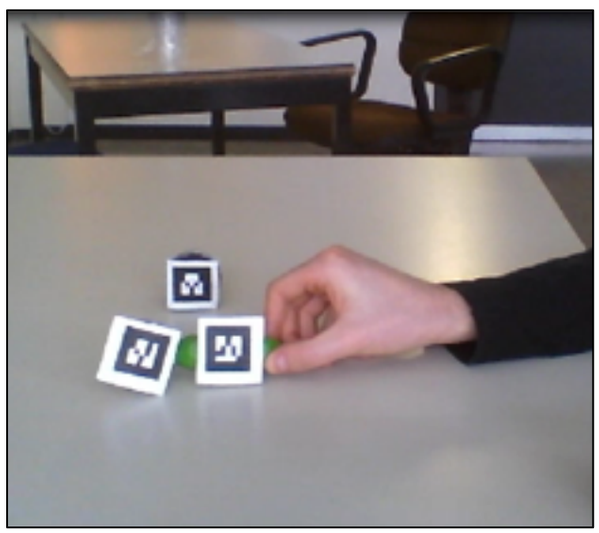
Learning : fully observable

No continuous distributions

Relational Tracking



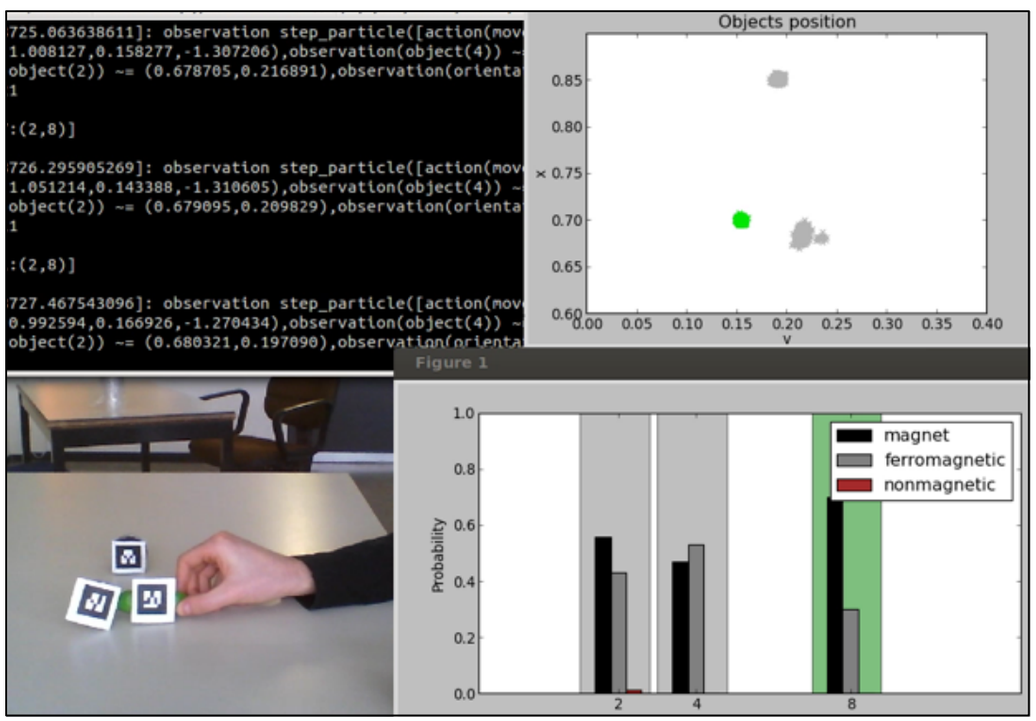
- Track people or objects over time? Even if temporarily hidden?
- Recognize activities?
- Infer object properties?

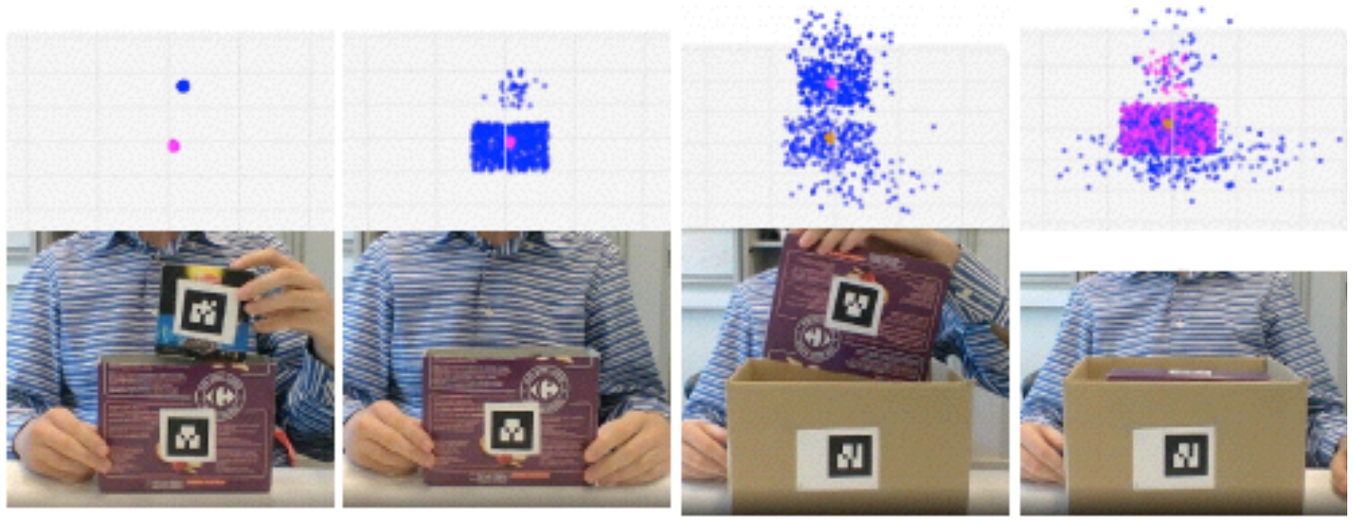


Relational State Estimation over Time

Magnetism scenario

- object tracking
- category estimation from interactions





(a) cube on the box (b) cube inside the box (c) rotated box on a beige box (d) cube and box inside the beige box

Box scenario

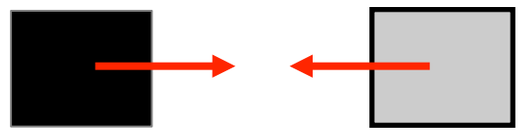
- object tracking even when invisible
- estimate spatial relations

[Nitti et al, IROS 13]

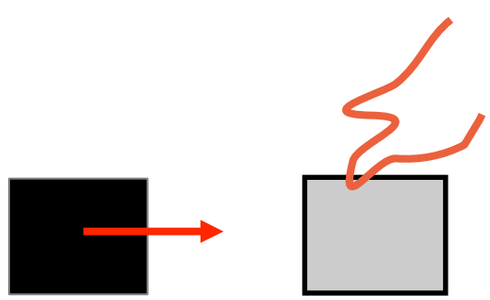
Magnetic scenario

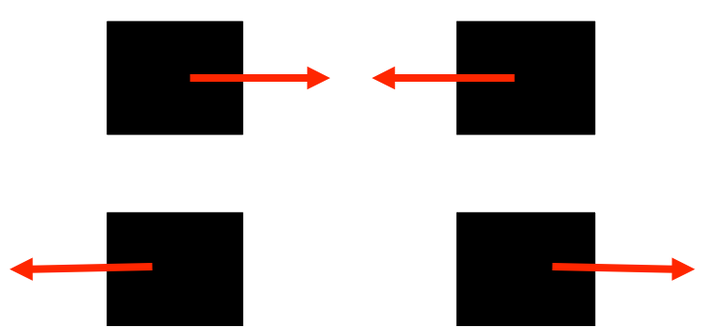
- 3 object types: magnetic, ferromagnetic, nonmagnetic

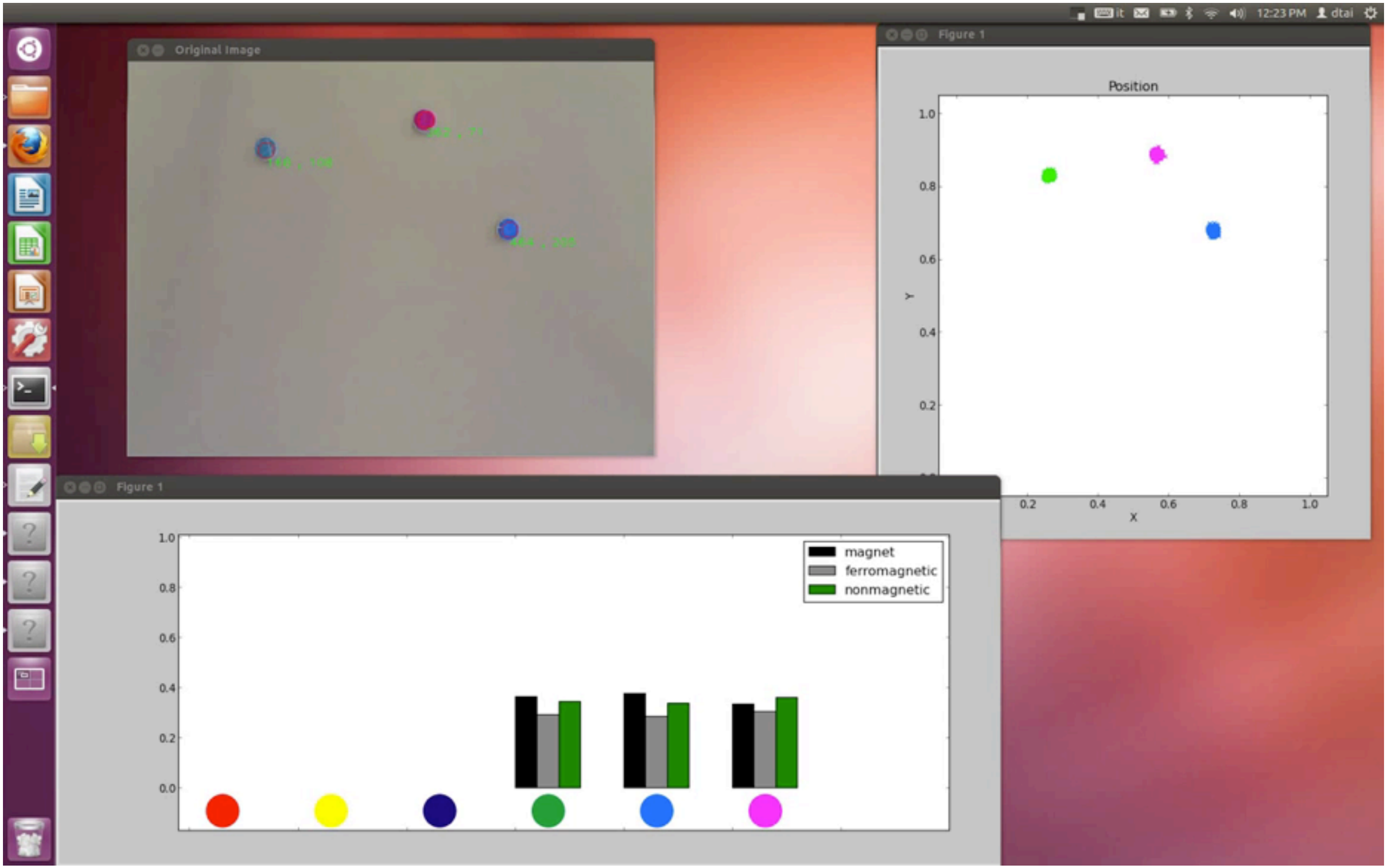
- Nonmagnetic objects do not interact
- A magnet and a ferromagnetic object attract each other

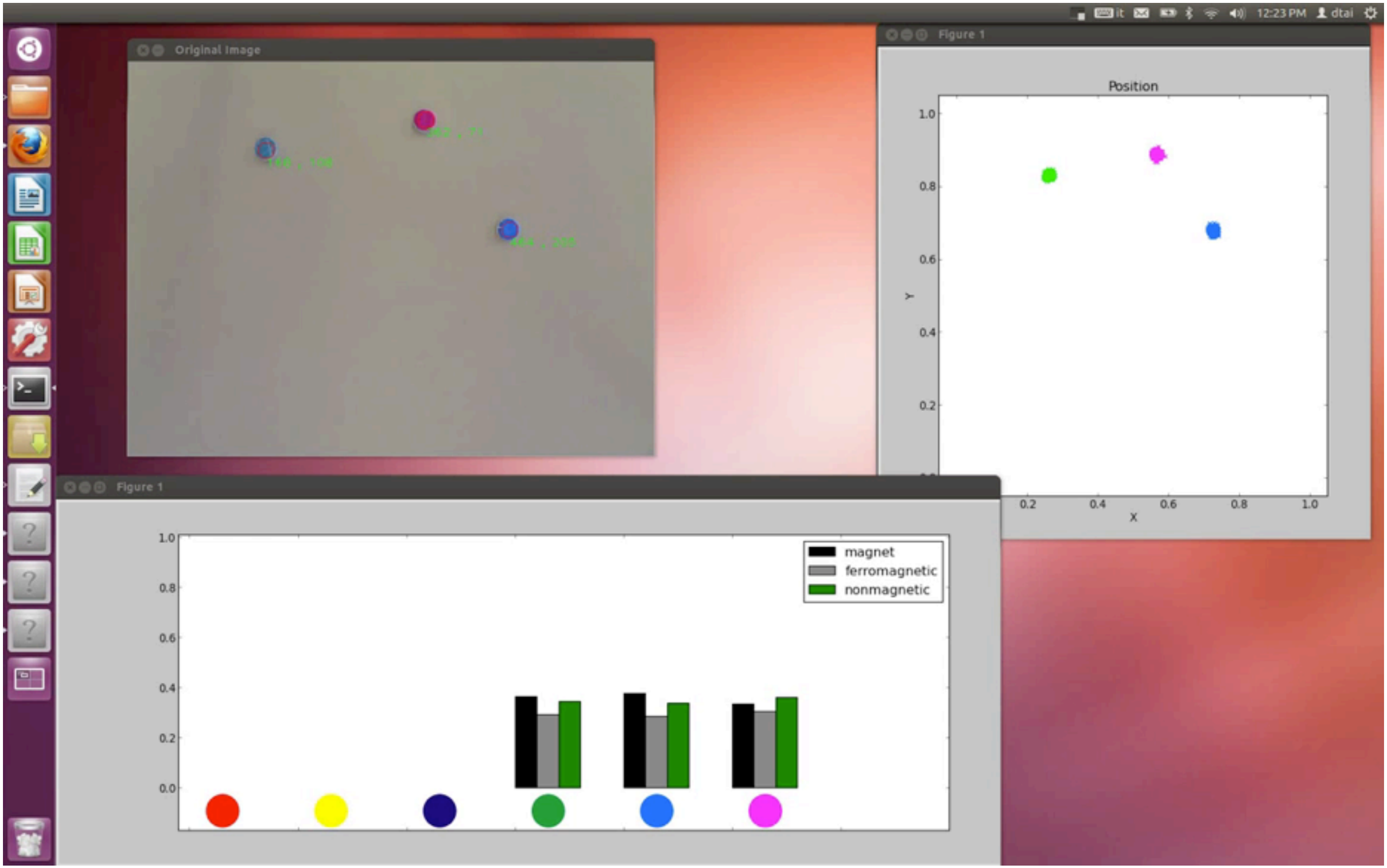


- Magnetic force that depends on the distance
- If an object is held magnetic force is compensated.






it
12:23 PM
dtai
Original Image
462 , 71
160 , 108
464 , 205
Figure 1
Position
1.0
0.8
0.6
0.4
0.2
Y
0.2
0.4
0.6
0.8
1.0
X
Figure 1
1.0
0.8
0.6
0.4
0.2
0.0
magnet
ferromagnetic
nonmagnetic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1.0
X
Figure 1
1.0
0.8
0.6
0.4
0.2
0.0
magnet
ferromagnetic
nonmagnetic

Magnetic scenario

- 3 object types: magnetic, ferromagnetic, nonmagnetic

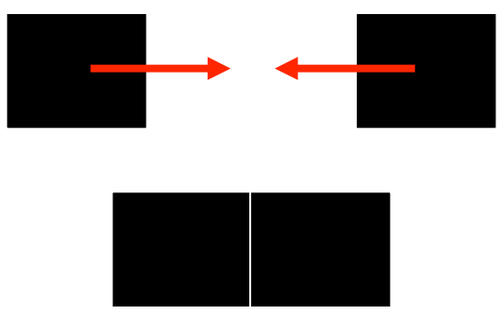
$$\text{type}(X)_t \sim \text{finite}([1/3\text{:magnet}, 1/3\text{:ferromagnetic}, 1/3\text{:nonmagnetic}]) \leftarrow \text{object}(X).$$

- 2 magnets attract or repulse

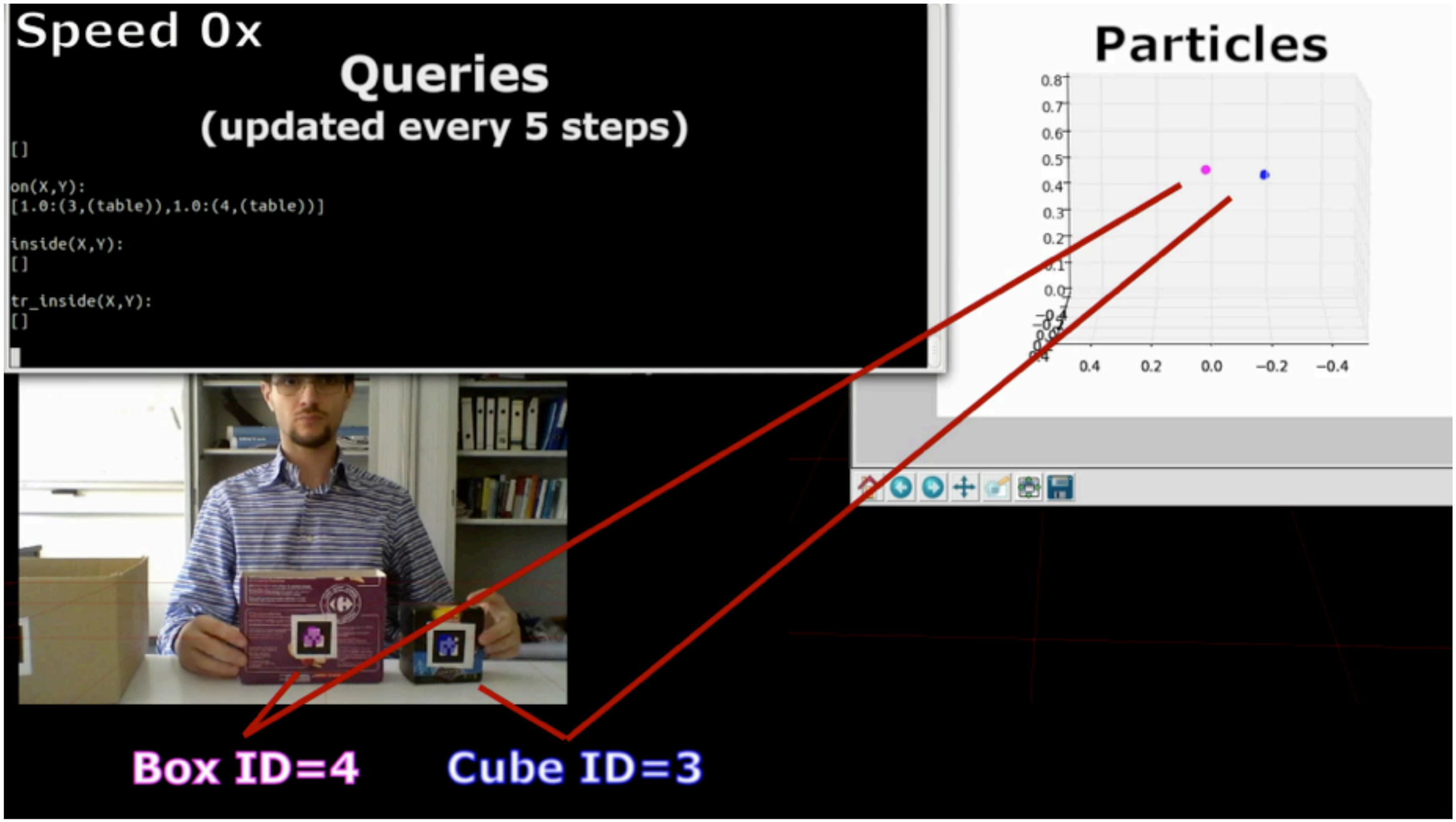
$$\text{interaction}(A,B)_t \sim \text{finite}([0.5\text{:attraction}, 0.5\text{:repulsion}]) \leftarrow \text{object}(A), \text{object}(B), A<B, \text{type}(A)_t = \text{magnet}, \text{type}(B)_t = \text{magnet}.$$

- Next position after attraction

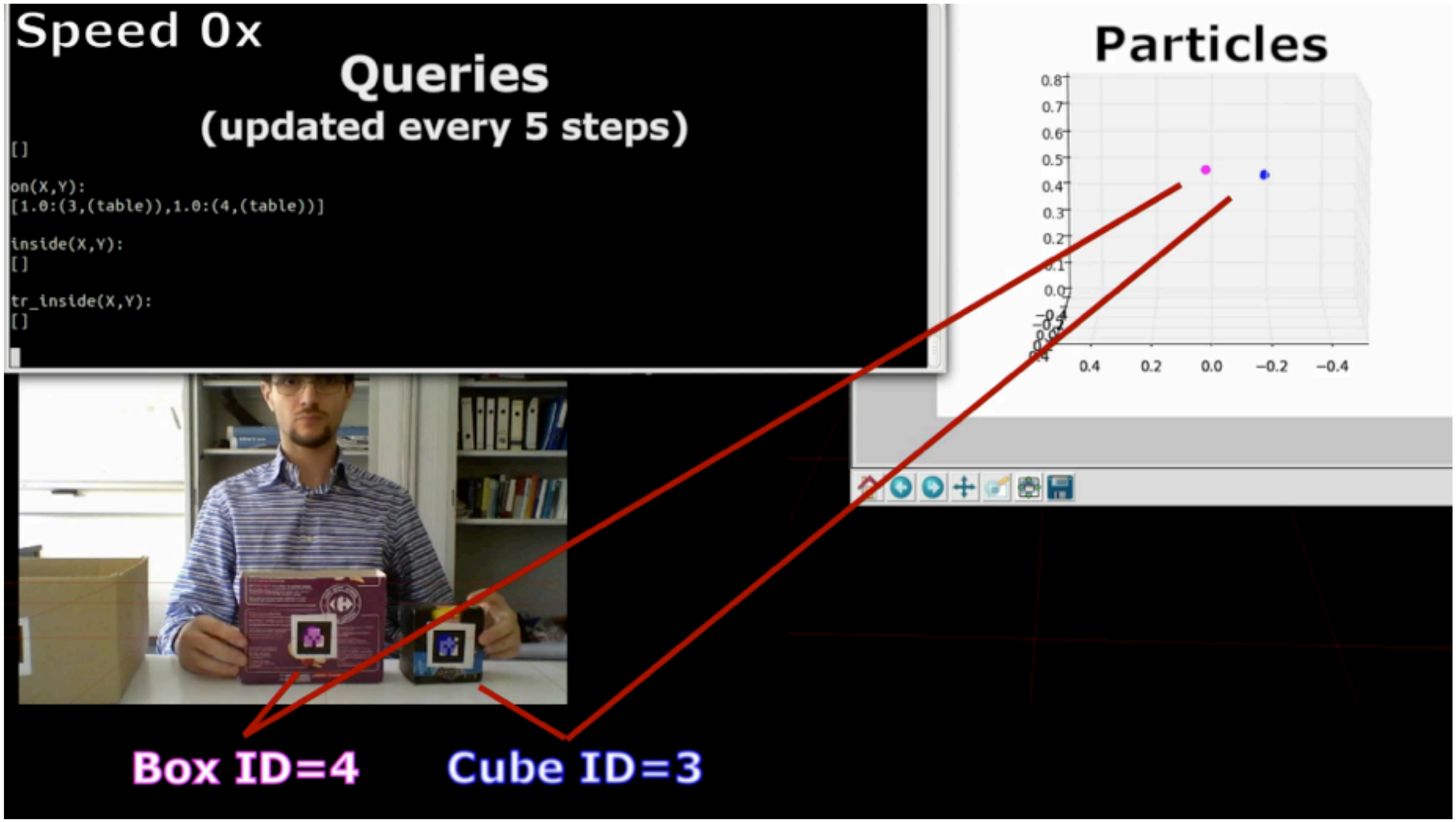
$$\text{pos}(A)_{t+1} \sim \text{gaussian}(\text{middlepoint}(A,B)_t, \text{Cov}) \leftarrow \text{near}(A,B)_t, \text{not}(\text{held}(A)), \text{not}(\text{held}(B)), \text{interaction}(A,B)_t = \text{attr}, c/\text{dist}(A,B)_t^2 > \text{friction}(A)_t.$$



$$\text{pos}(A)_{t+1} \sim \text{gaussian}(\text{pos}(A)_t, \text{Cov}) \leftarrow \text{not}(\text{attraction}(A,B)).$$


Speed 0x
Queries
(updated every 5 steps)
[]
on(X,Y):
[1.0:(3,(table)),1.0:(4,(table))]
inside(X,Y):
[]
tr_inside(X,Y):
[]
Particles
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.4
0.2
0.0
−0.2
−0.4
Box ID=4
Cube ID=3

IROS 13


Speed 0x
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[]
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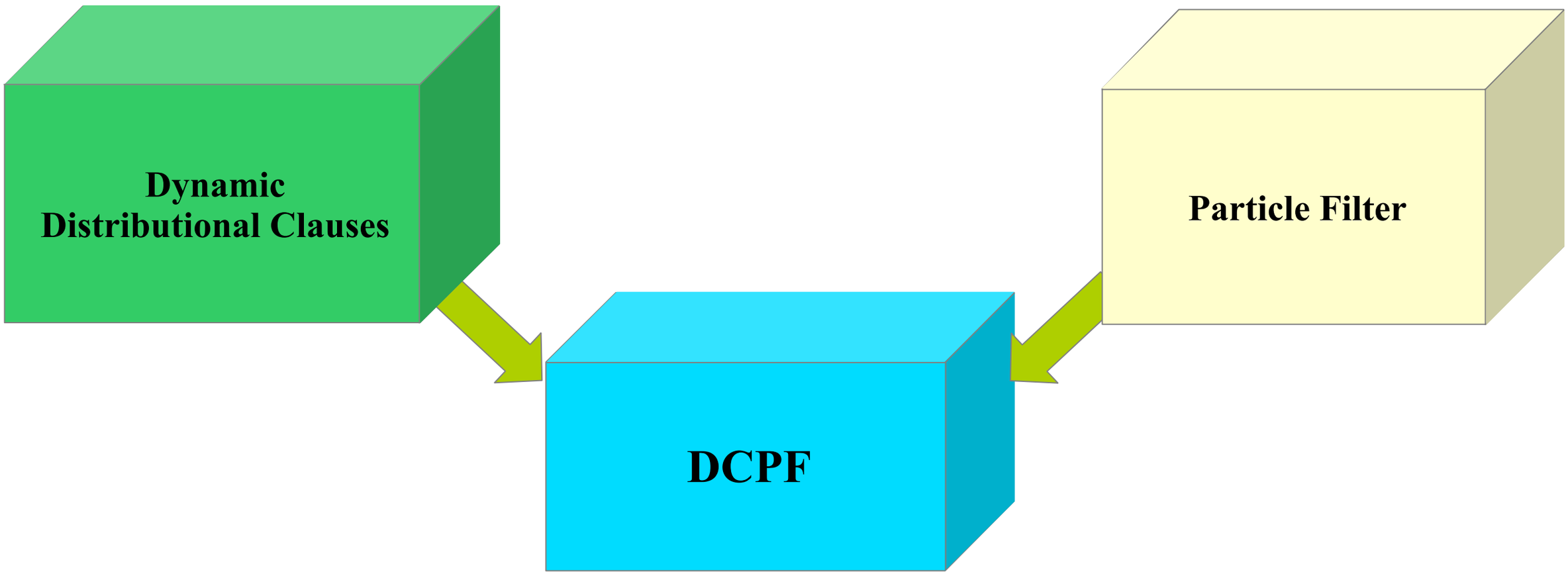
0.5
0.4
0.3
0.2
0.4
0.2
0.0
−0.2
−0.4
Box ID=4
Cube ID=3

IROS 13

DC Particle Filter (DCPF)



Goal

Flexible (relational) state representation

Fast inference (state estimation) in general models

"A particle filter for hybrid relational domains" IROS 2013
D. Nitti, T. De Laet, L. De Raedt

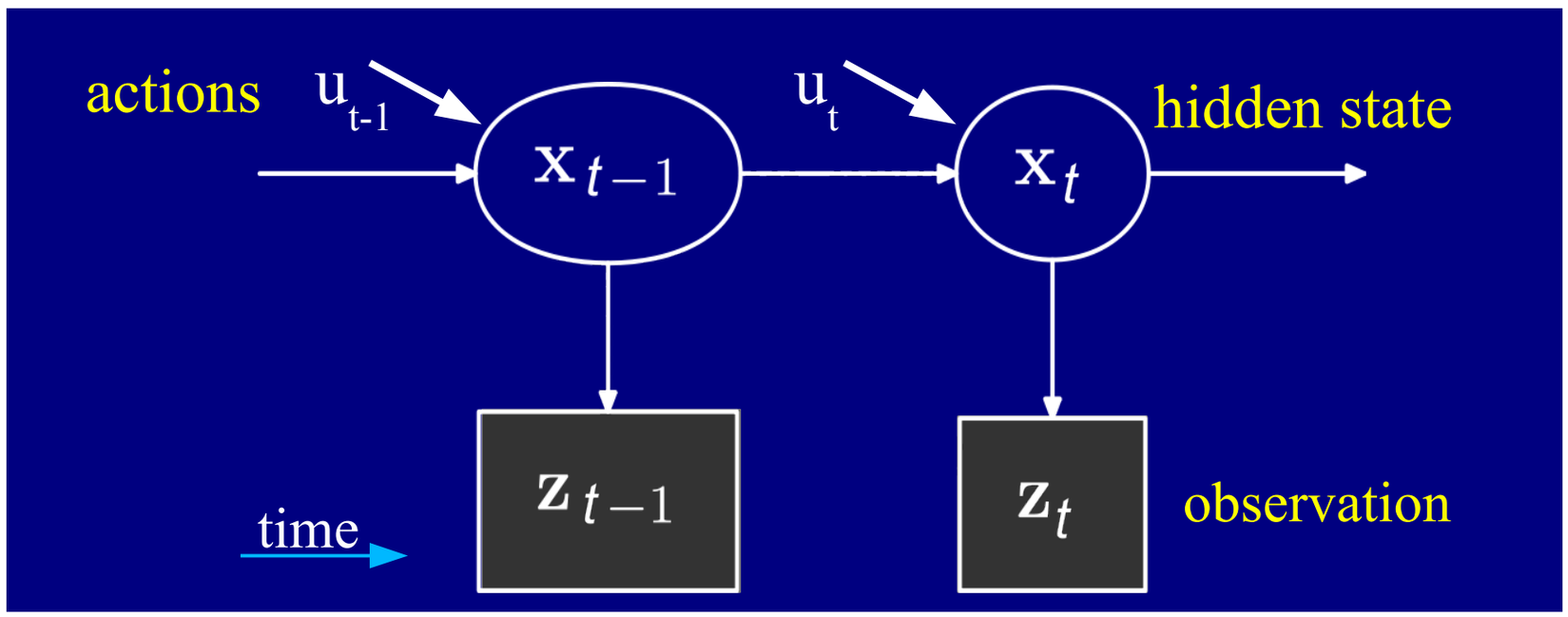
Dynamic Distributional Clauses

Prior distribution $p(x_0)$

State transition model $p(x_t|x_{t-1},u_t)$

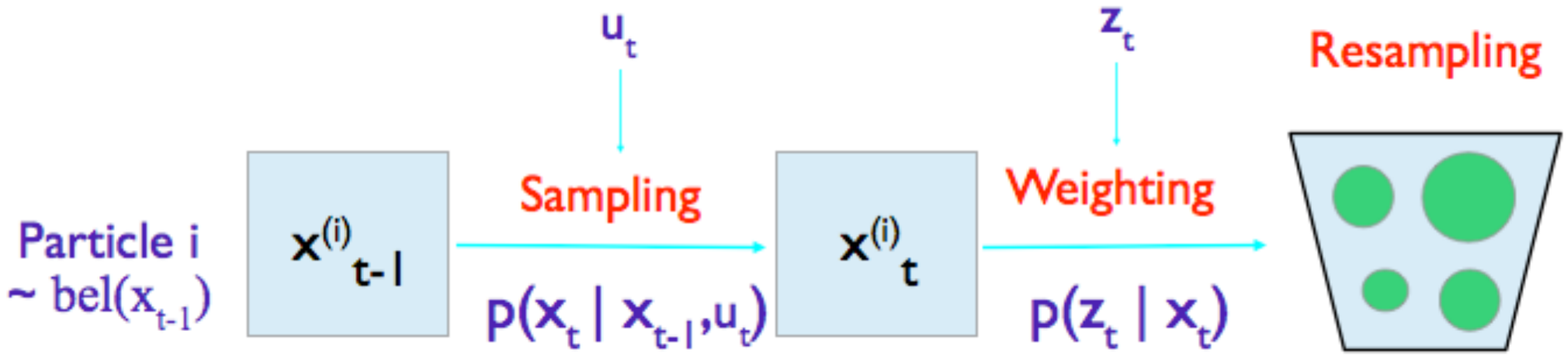
Measurement model $p(z_t|x_t)$

Other rules: $p(x'_t|x''_t)$



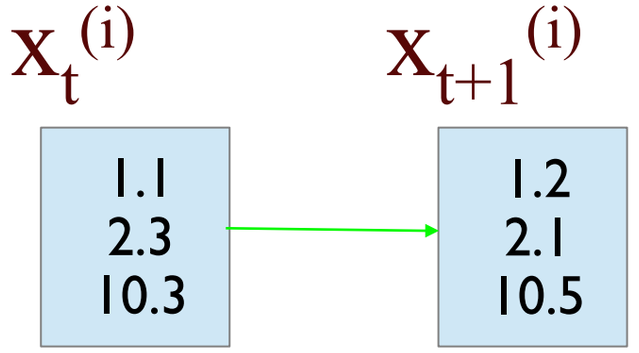
Particle Filter
(Sequential Monte Carlo)

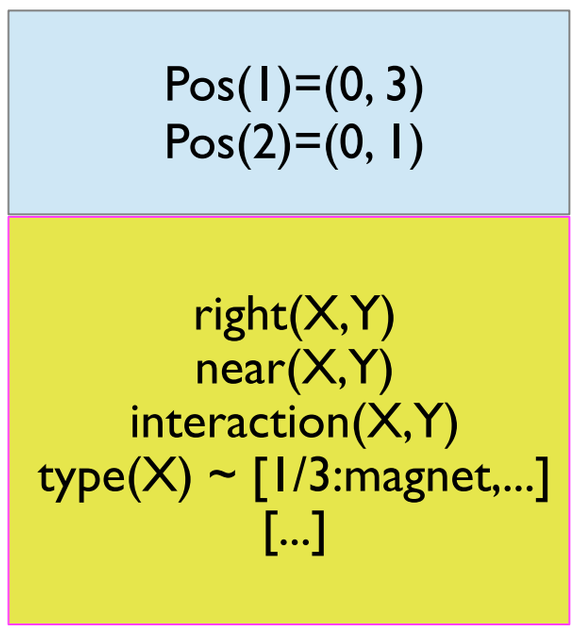
- Based on sampling → approximate inference
- Particles (samples) to represent bel(x_t)



Classical Particle Filter vs DCPF

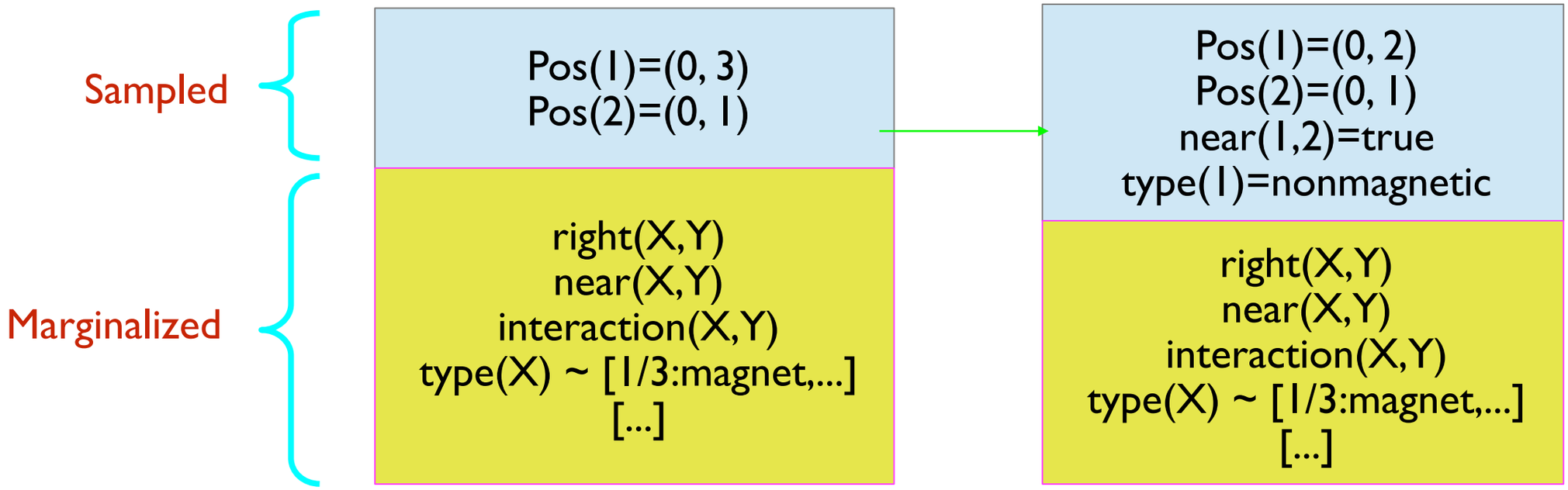
- Classical PF
  - Fixed set of random variables
  - Update the entire state
- DCPF
  - **Adaptive state** (particle): the number of facts / random variables can change over time
  - Particles are partial interpretations
  - Expressive language



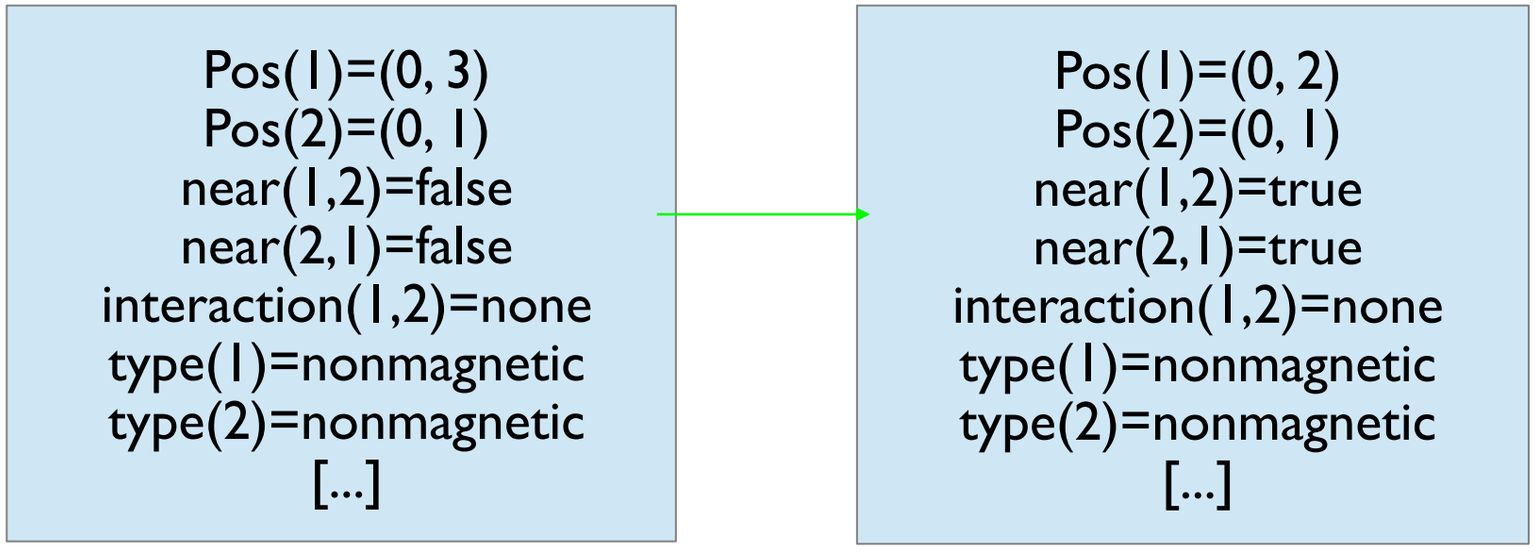


Optimized inference: partial state

Distributional Clauses Particle Filter (DCPF)



Classical particle filter



Inference in DCPF

Two steps:

Query $p(z_{t+1}|x_{t+1})$ (weighting + part of sampling step)

Query $p(x_{t+1}|x_t, u_{t+1})$ (to complete the sampling step)

particles are partial interpretations

bel(x_t) fully represented by $\{x_t^{(i)}\} \cup$ Program

History $\{x_{0:t-1}^{(i)}\}$ not necessary

Issue: particles (interpretations) may grow till becoming complete

Ongoing Work

- Parameter learning [Nitti, ICRA 2014]
- Integrate with planning [Nitti ECML, EWRL 15]
- Larger Experiments
- Connection to probabilistic programming
- Applications in robotics (also to learn affordances)

ProbLog for activity recognition from video

CAVIAR-INRIA human activity dataset

28 videos
≈ 26.500 frames

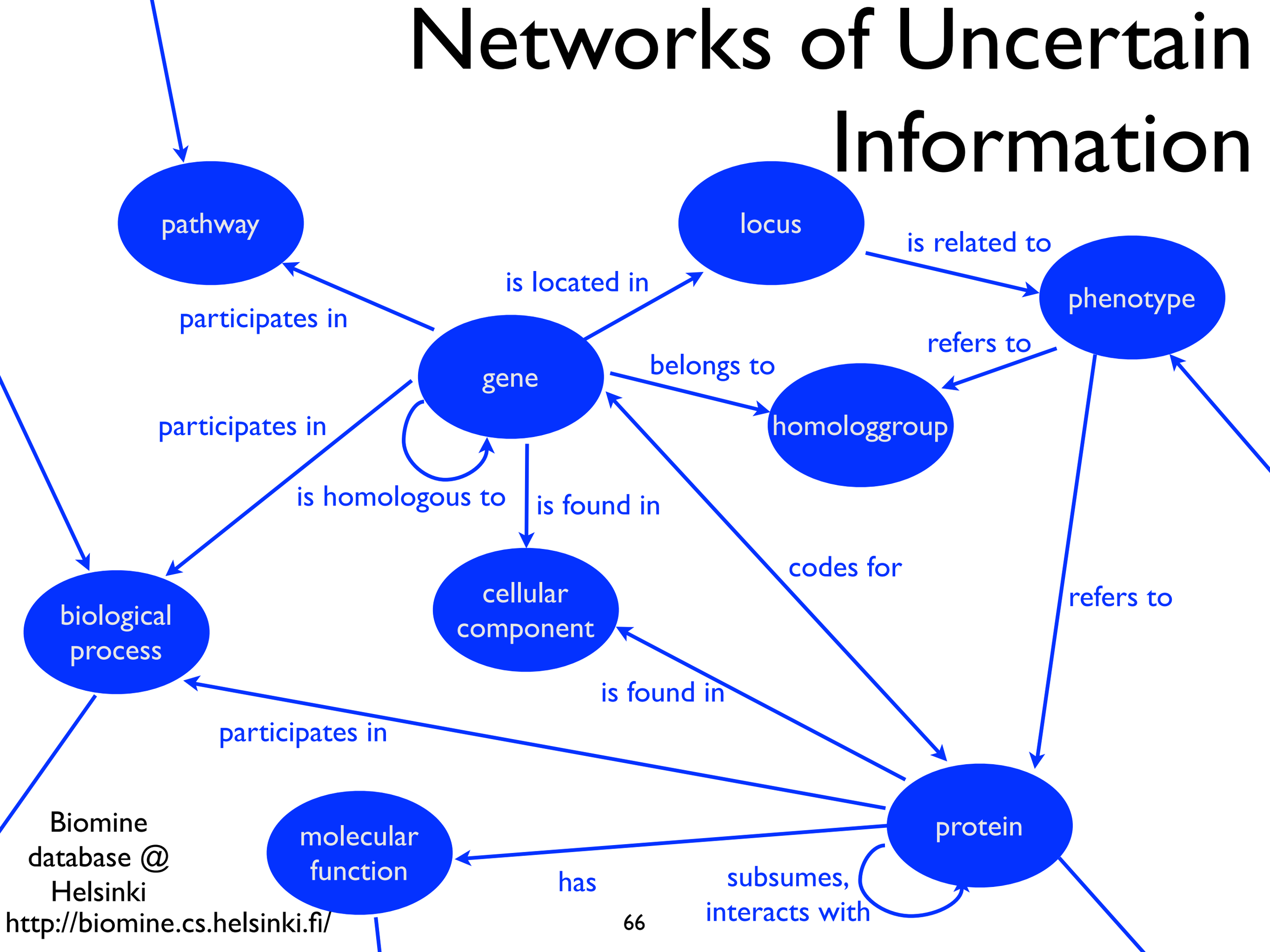
- Separation between low-level events (LLE) and high-level events (HLE)
  - LLE: *walking, running, active, inactive, abrupt*
  - HLE: *meeting, moving, fighting, leaving_object*
- Probabilistic Logic approach: *Event Calculus in ProbLog* (Prob-EC) to infer the high-level events from an **algebra** of low-level events.
- Example:

$$initiatedAt(fighting(P_1, P_2) = true, T) \leftarrow$$
$$happensAt(abrupt(P_1), T),$$
$$holdsAt(close(P_1, P_2, 44) = true, T),$$
$$not\ happensAt(inactive(P_2), T).$$

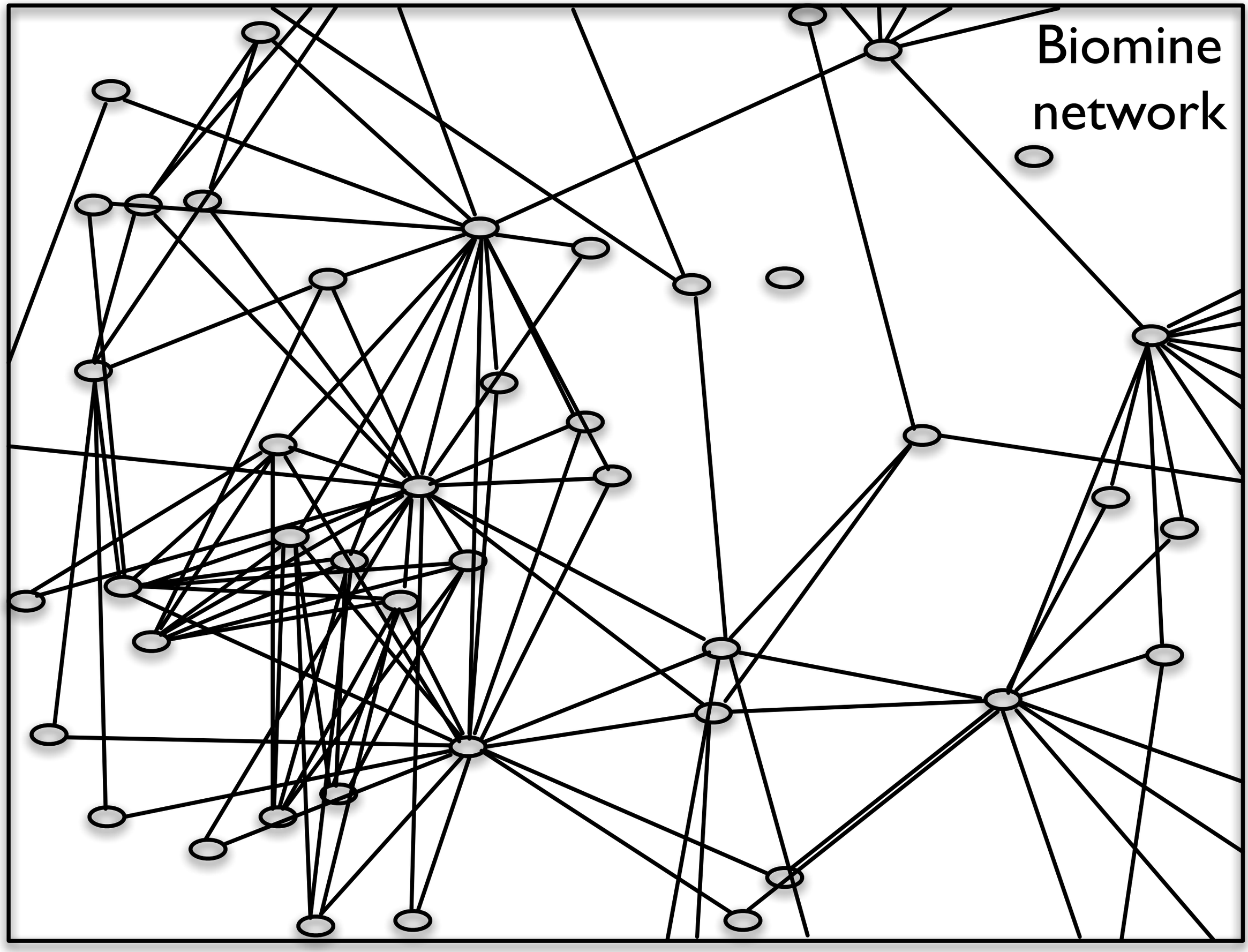
[Skarlatidis et al, TPLP 13]

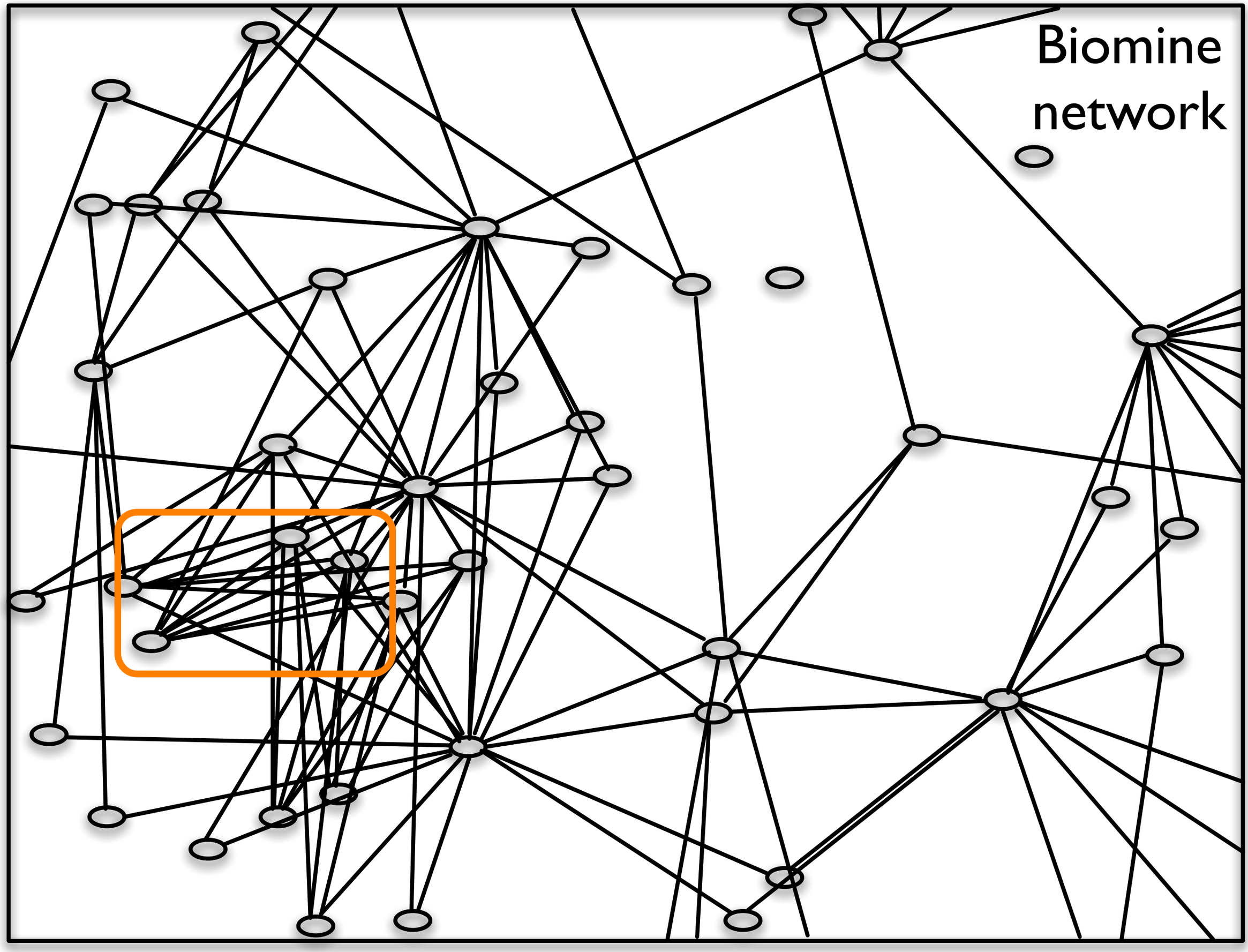
Decisions

Networks of Uncertain Information

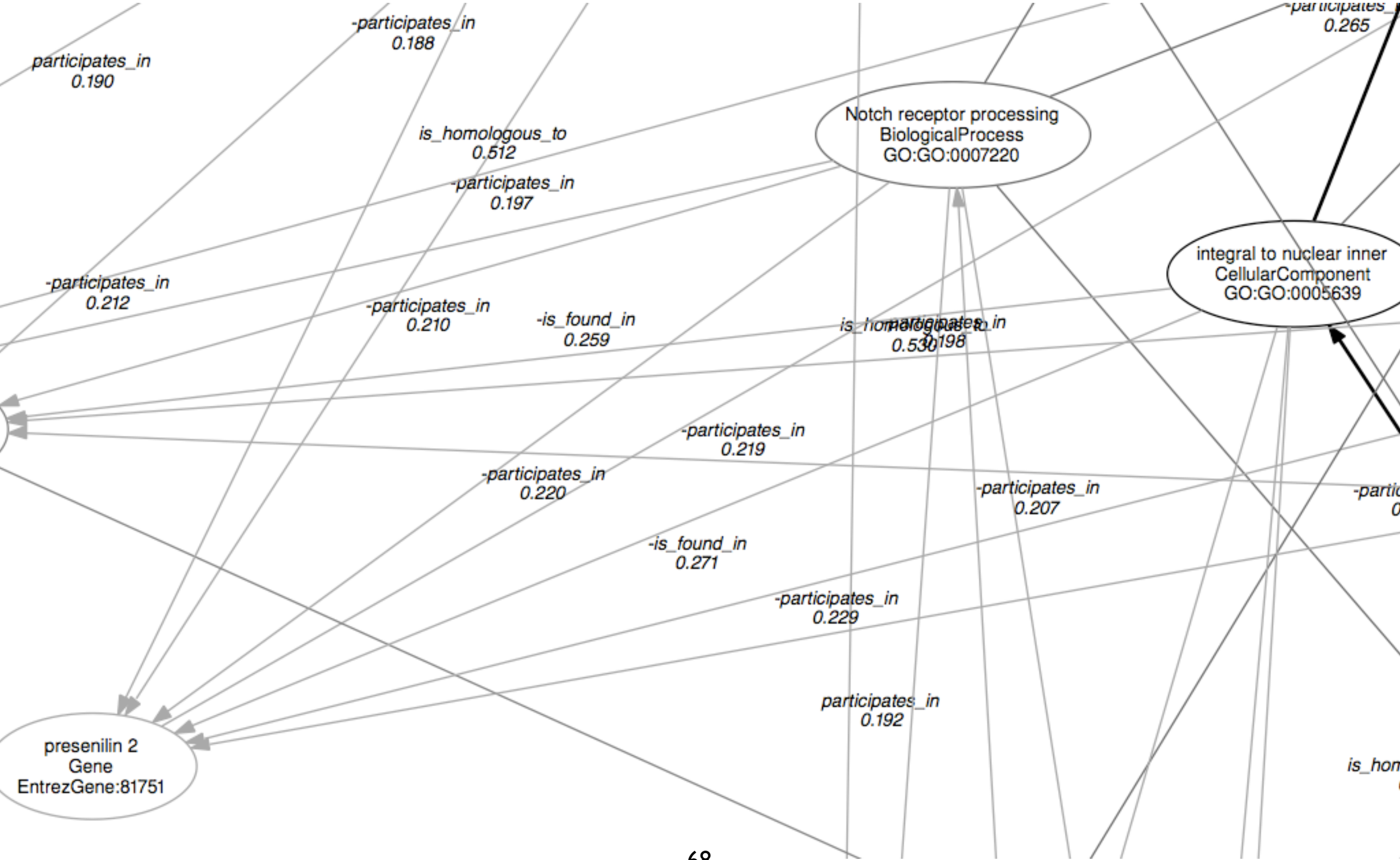


Biomine database @ Helsinki
http://biomine.cs.helsinki.fi/


Biomine
network

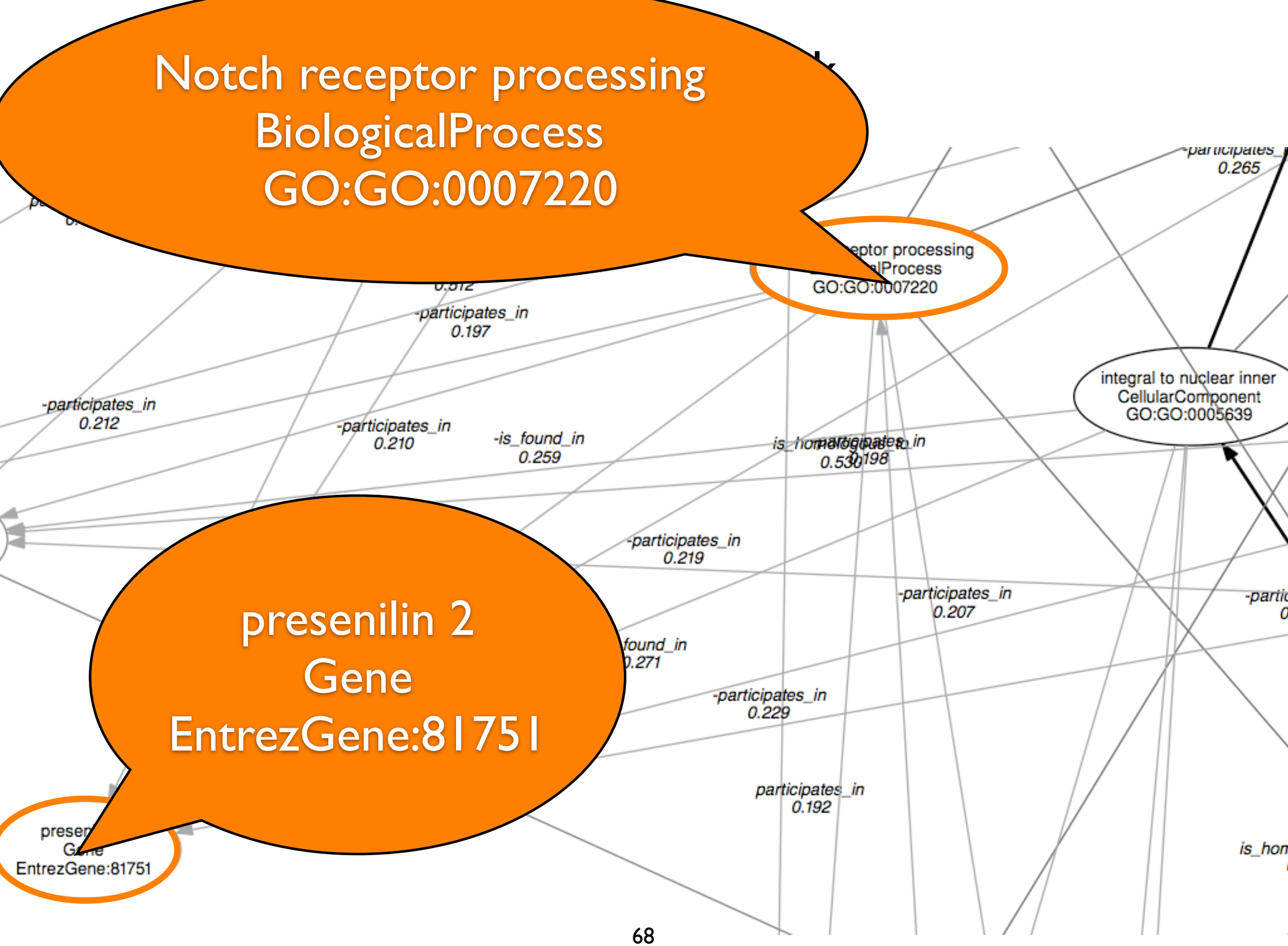

Biomine
network

Biomine Network

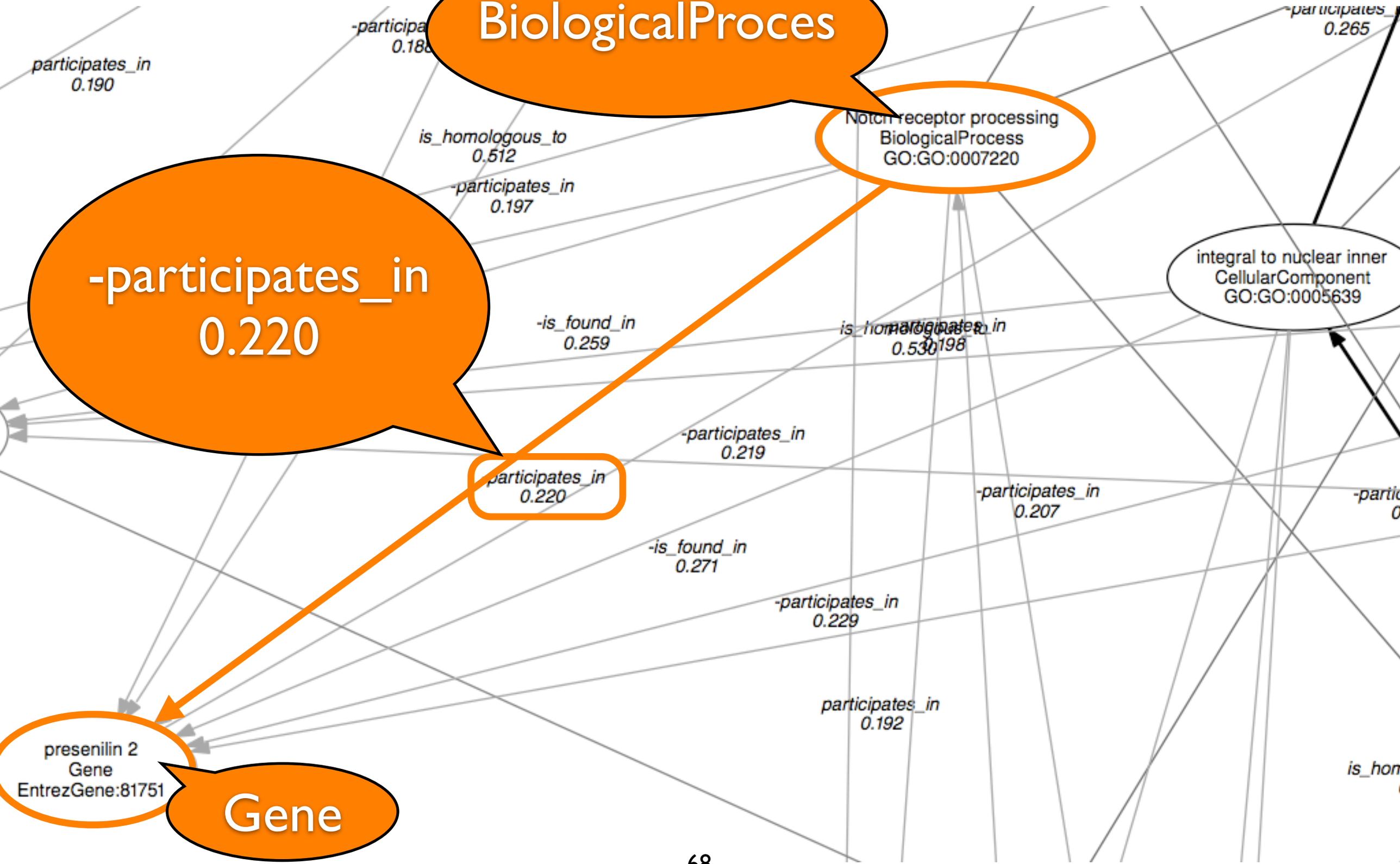


Notch receptor processing
BiologicalProcess
GO:GO:0007220

presenilin 2
Gene
EntrezGene:81751



Biomine Network



Graphs & Randomness

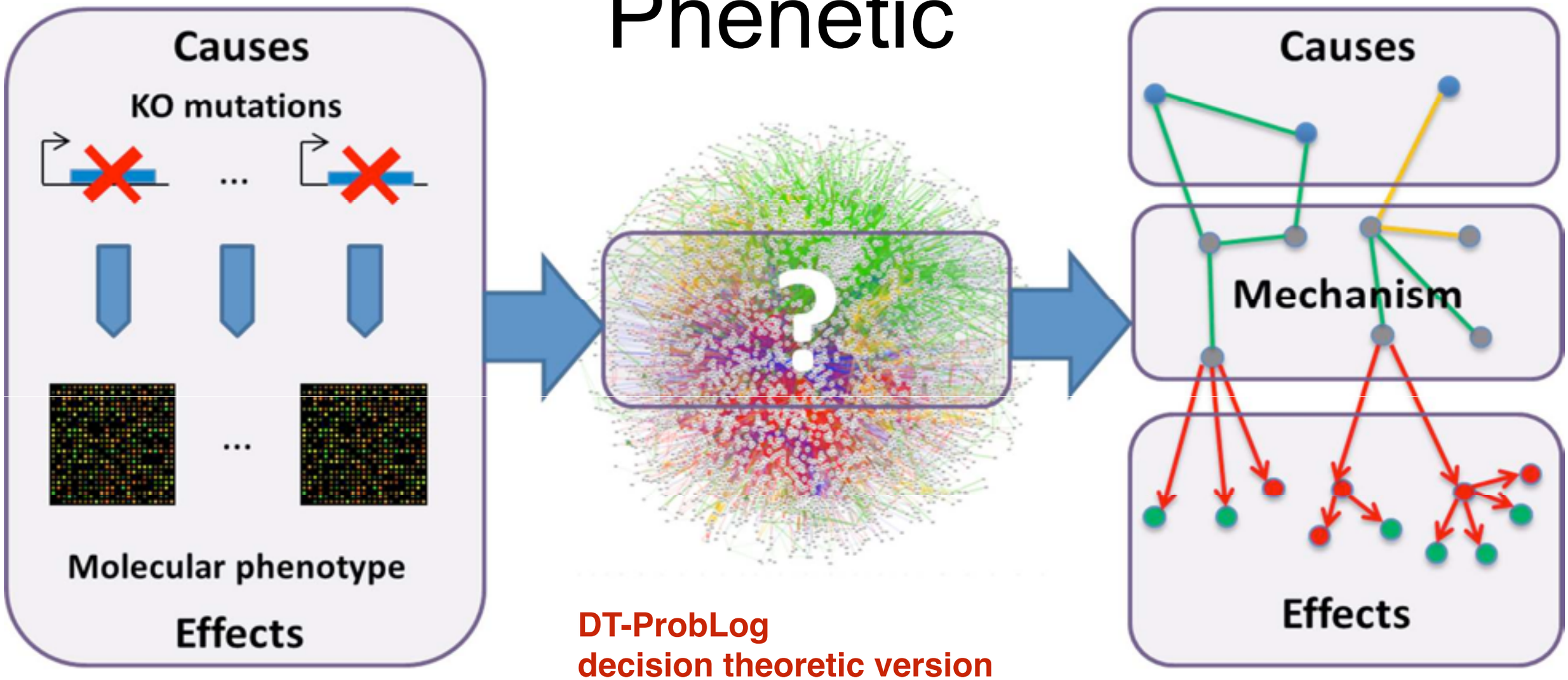
ProbLog, Phenetic, Prism, ICL, Probabilistic Databases, ...

- all based on a "random graph" model

Stochastic Logic Programs, ProPPR, PCFGs, ...

- based on a "random walk" model
- connected to PageRank

Phenetic



DT-ProbLog
decision theoretic version

- Causes: Mutations
  - All related to similar phenotype
- Effects: Differentially expressed genes
- 27 000 cause effect pairs

- Interaction network:
  - 3063 nodes
    - Genes
    - Proteins
  - 16794 edges
    - Molecular interactions
    - Uncertain

- Goal: connect causes to effects through common subnetwork
  - = Find mechanism
- Techniques:
  - DTProbLog [Van den Broeck]
  - Approximate inference

Can we find the mechanism connecting causes to effects?

[De Maeyer et al., Molecular Biosystems 13, NAR 15]

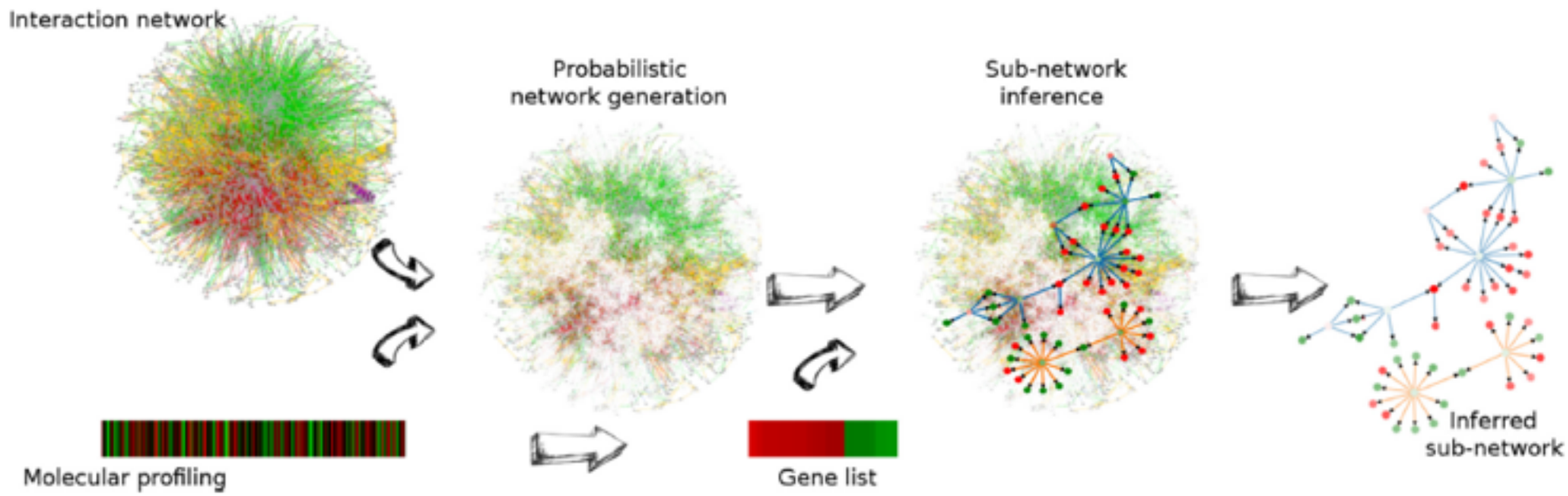
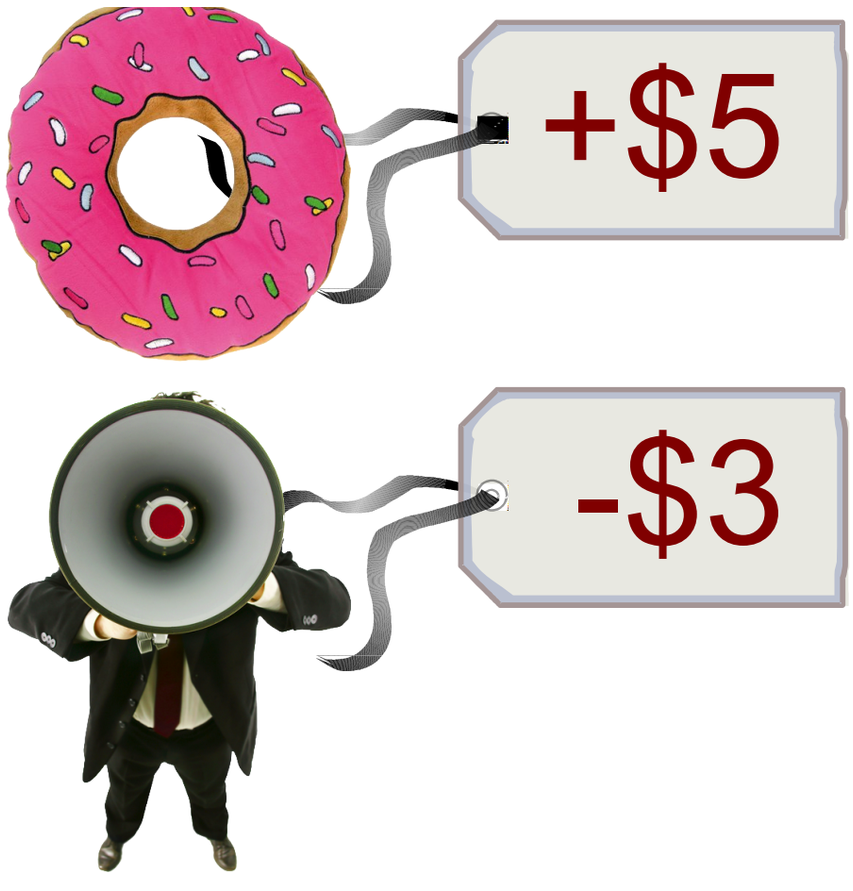
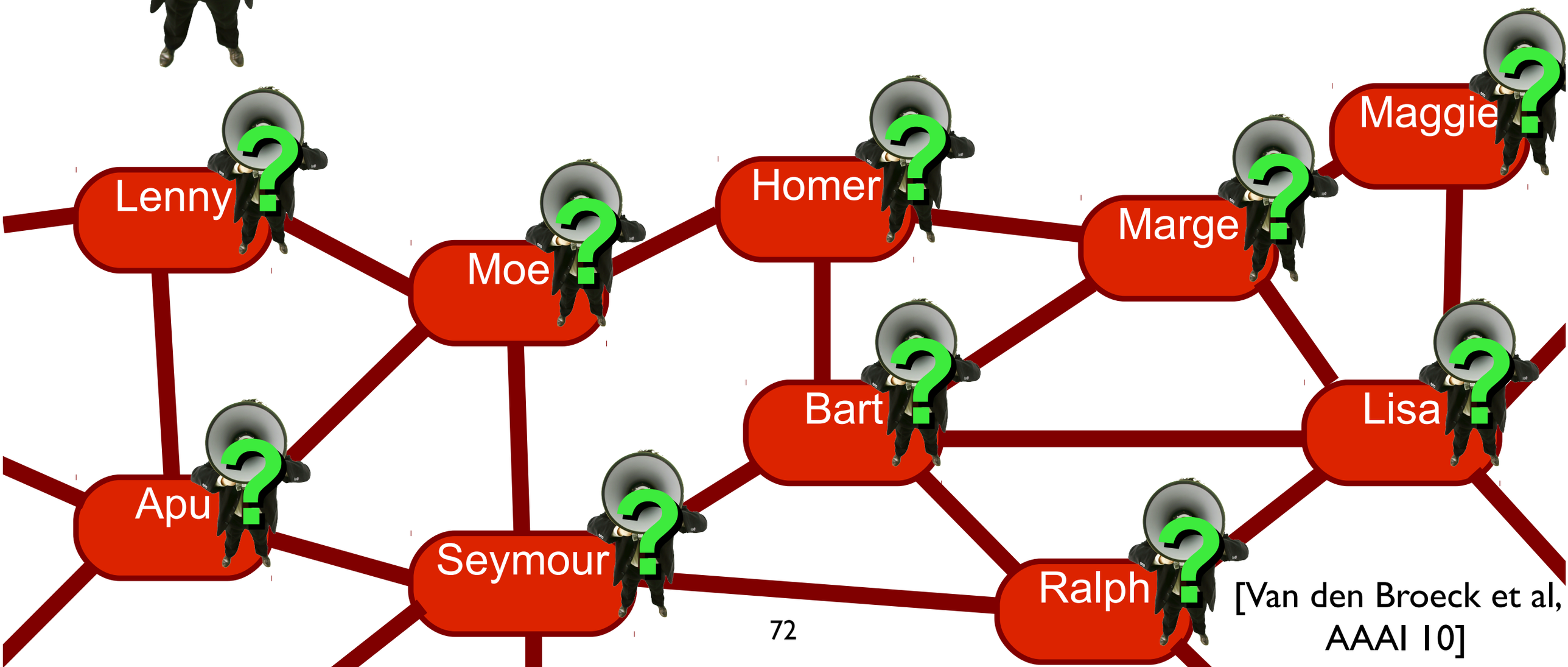


Figure 1. Overview of PheNetic, a web service for network-based interpretation of 'omics' data. The web service uses as input a genome wide interaction network for the organism of interest, a user generated molecular profiling data set and a gene list derived from these data. Interaction networks for a wide variety of organisms are readily available from the web server. Using the uploaded user-generated molecular data the interaction network is converted into a probabilistic network: edges receive a probability proportional to the levels measured for the terminal nodes in the molecular profiling data set. This probabilistic interaction network is used to infer the sub-network that best links the genes from the gene list. The inferred sub-network provides a trade-off between linking as many genes as possible from the gene list and selecting the least number of edges.

Viral Marketing

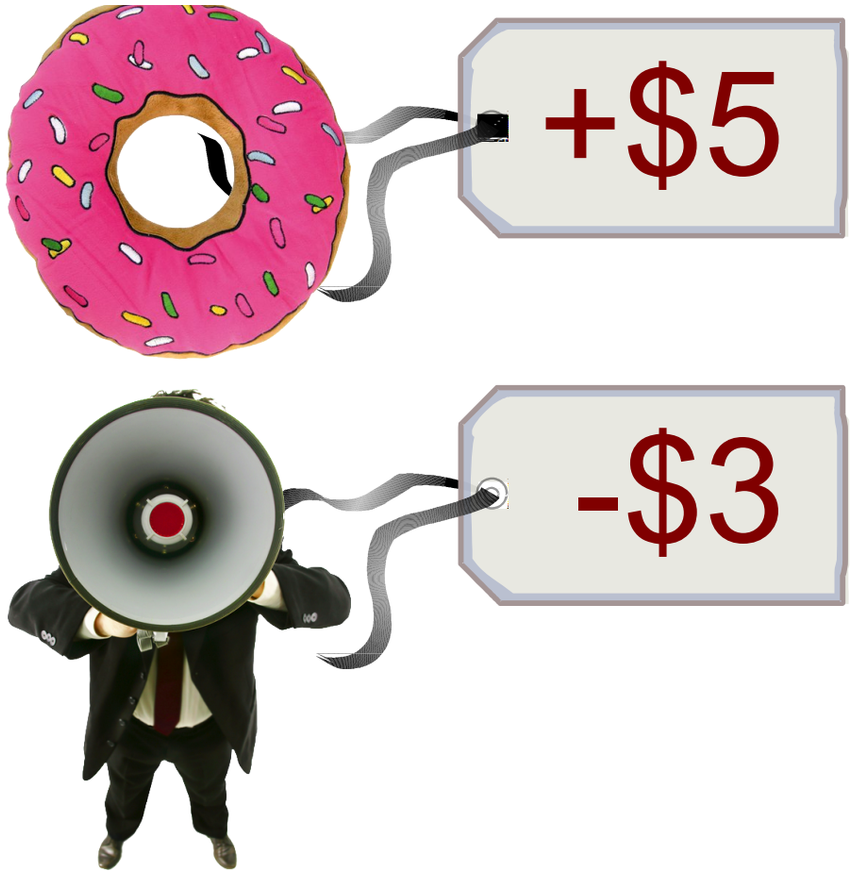


Which advertising strategy maximizes expected profit?

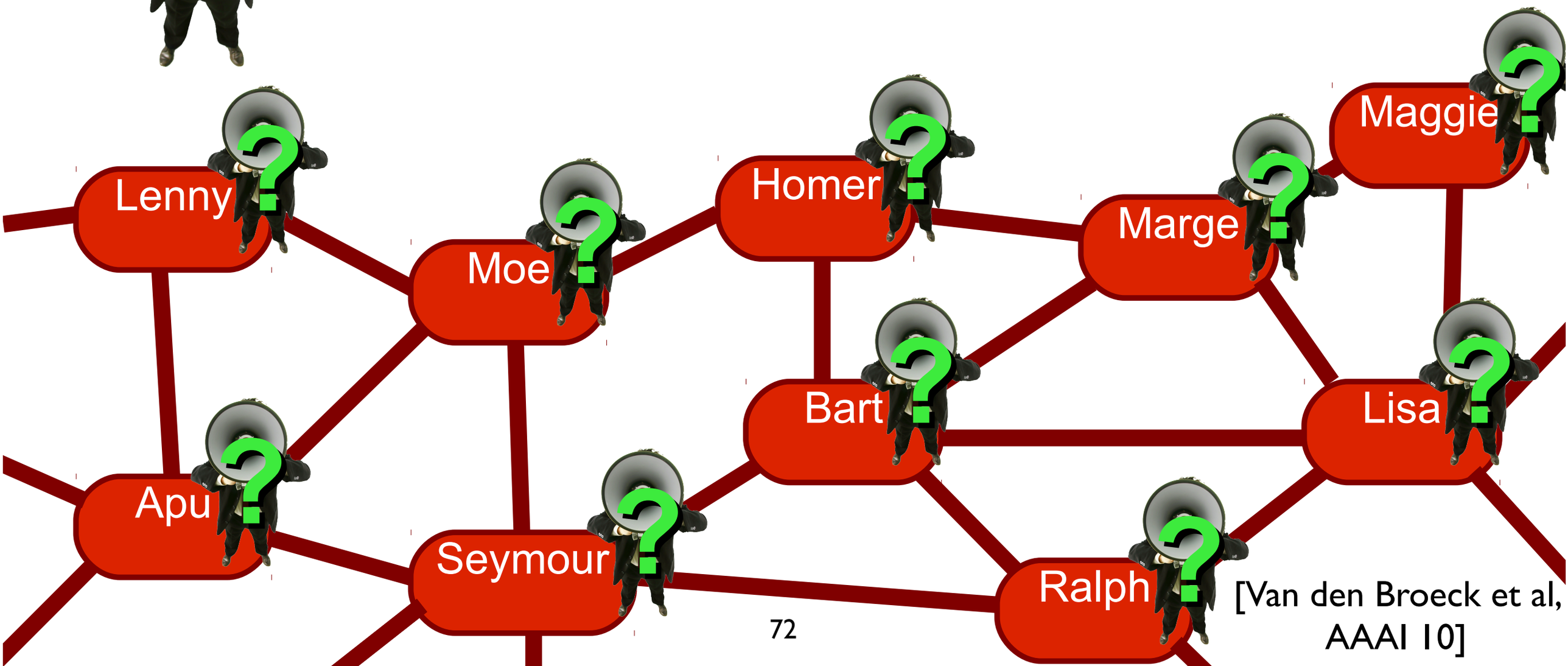


[Van den Broeck et al, AAAI 10]

Viral Marketing

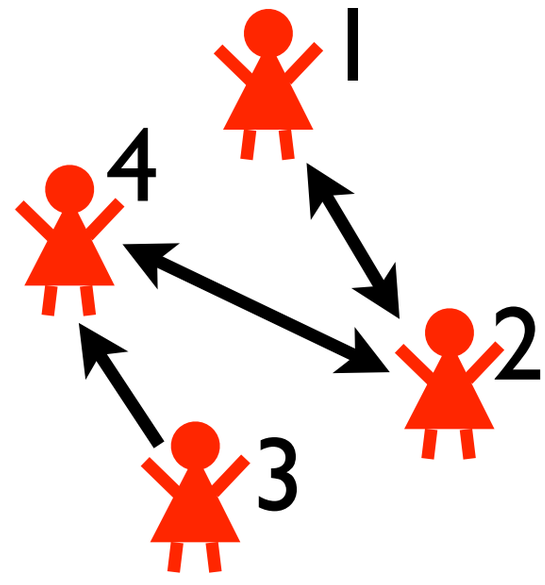


decide truth values of some atoms



[Van den Broeck et al, AAAI 10]

DTProbLog



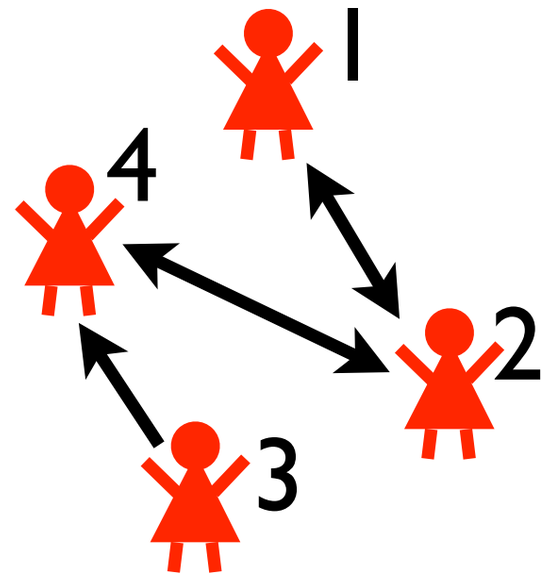

```
person(1).
person(2).
person(3).
person(4).
```

```
friend(1,2).
friend(2,1).
friend(2,4).
friend(3,4).
friend(4,2).
```

DTProbLog

```
? :: marketed(P) :- person(P).
```

decision fact: true or false?

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buys(X) :- friend(X,Y), buys(Y), buy_trust(X,Y).
buys(X) :- marketed(X), buy_marketing(X).
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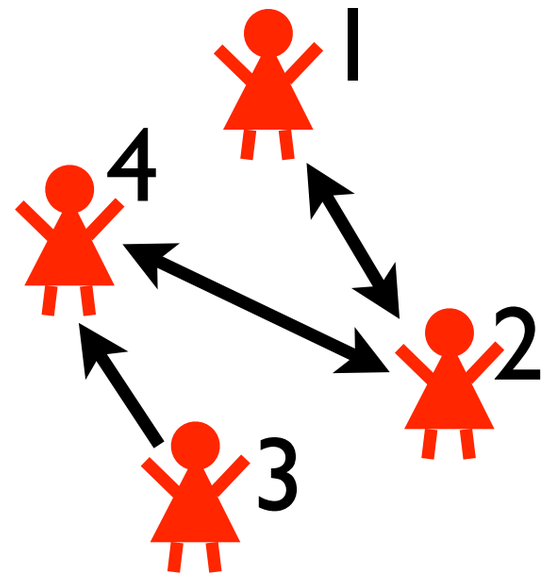
probabilistic facts
+ logical rules

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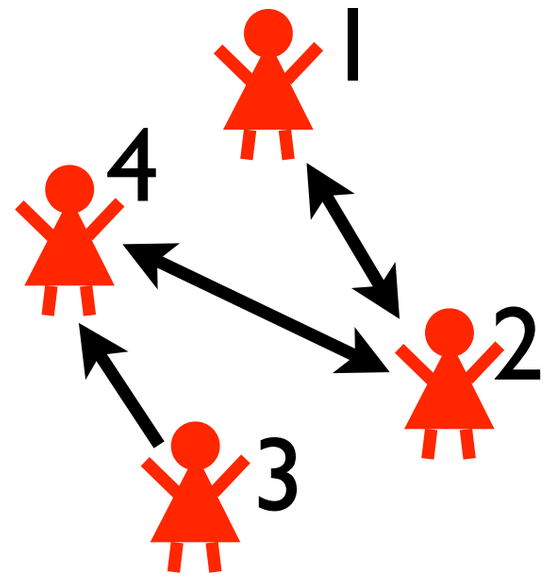


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buys(X) :- marketed(X), buy_marketing(X).
```

```
buys(P) => 5 :- person(P).
marketed(P) => -3 :- person(P).
```

utility facts: cost/reward if true

```
person(1).
person(2).
person(3).
person(4).

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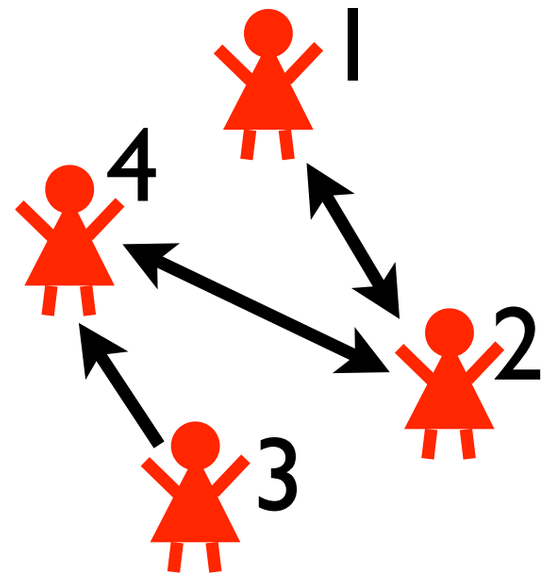
DTProbLog

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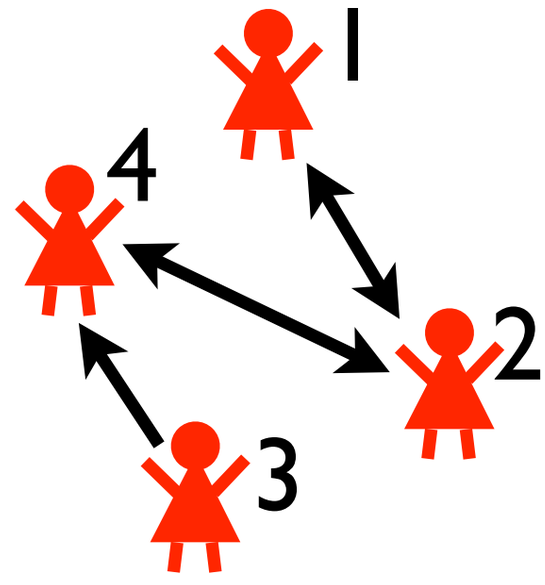


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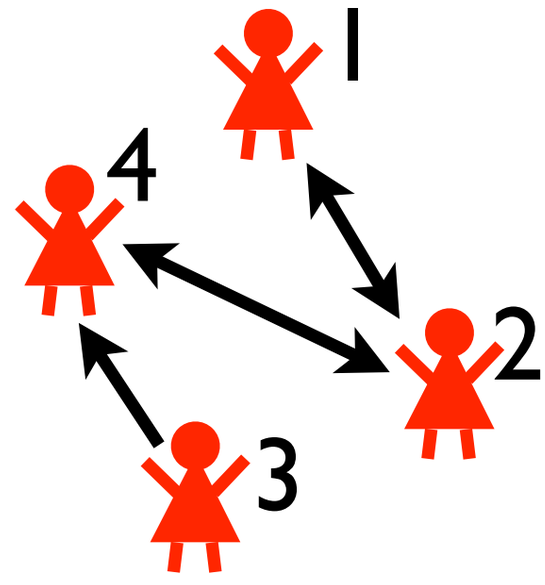


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friend(2,4).
friend(3,4).
friend(4,2).
```

```
marketed(1)        marketed(3)
```

DTProbLog

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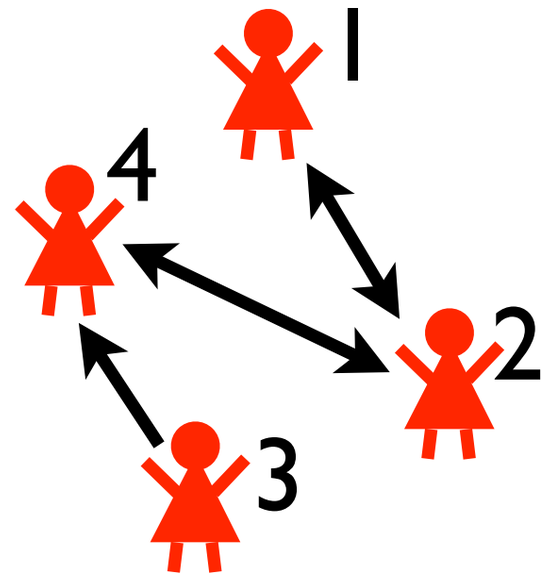


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friend(4,2).
```

```
marketed(1)        marketed(3)

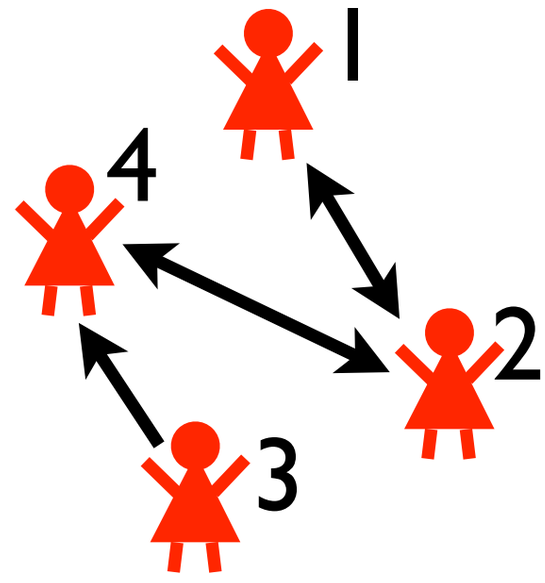
    bt(2,1)   bt(2,4)          bm(1)
```

DTProbLog

```
? :: marketed(P) :- person(P).

0.3 :: buy_trust(X,Y) :- friend(X,Y).
0.2 :: buy_marketing(P) :- person(P).

buys(X) :- friend(X,Y), buys(Y), buy_trust(X,Y).
buys(X) :- marketed(X), buy_marketing(X).
```

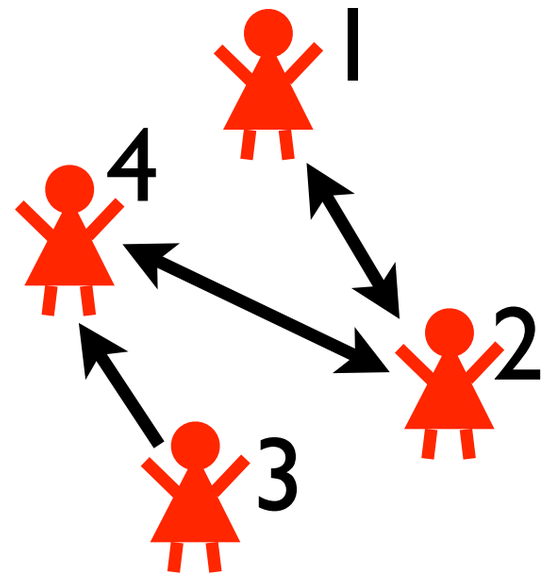



```
person(1).
person(2).
person(3).
person(4).
```

```
buys(P) => 5 :- person(P).
marketed(P) => -3 :- person(P).
```

```
friend(1,2).
friend(2,1).
friend(2,4).
friend(3,4).
friend(4,2).
```

DTProbLog




```
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0.2 :: buy_marketing(P) :- person(P).

buys(X) :- friend(X,Y), buys(Y), buy_trust(X,Y).
buys(X) :- marketed(X), buy_marketing(X).
```

```
person(1).
person(2).
person(3).
person(4).
```

```
buys(P) => 5 :- person(P).
marketed(P) => -3 :- person(P).
```

```
friend(1,2).
friend(2,1).
friend(2,4).
friend(3,4).
friend(4,2).
```

utility = −3 + −3 + 5 + 5 = 4

probability = 0.0032

```
marketed(1)          marketed(3)

    bt(2,1)    bt(2,4)          bm(1)

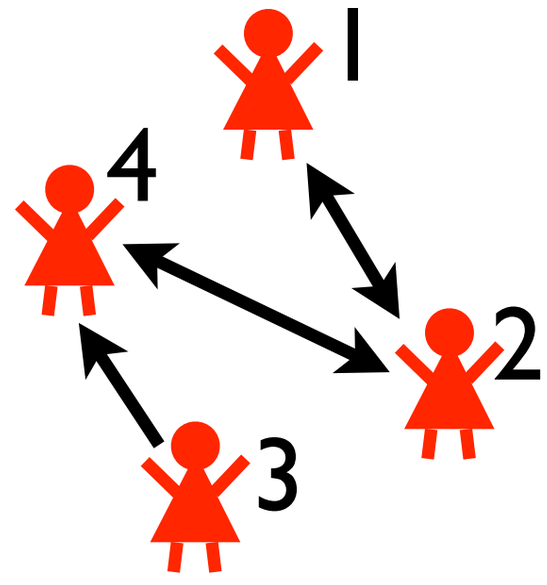
buys(1)      buys(2)
```

DTProbLog

```
? :: marketed(P) :- person(P).

0.3 :: buy_trust(X,Y) :- friend(X,Y).
0.2 :: buy_marketing(P) :- person(P).

buys(X) :- friend(X,Y), buys(Y), buy_trust(X,Y).
buys(X) :- marketed(X), buy_marketing(X).
```

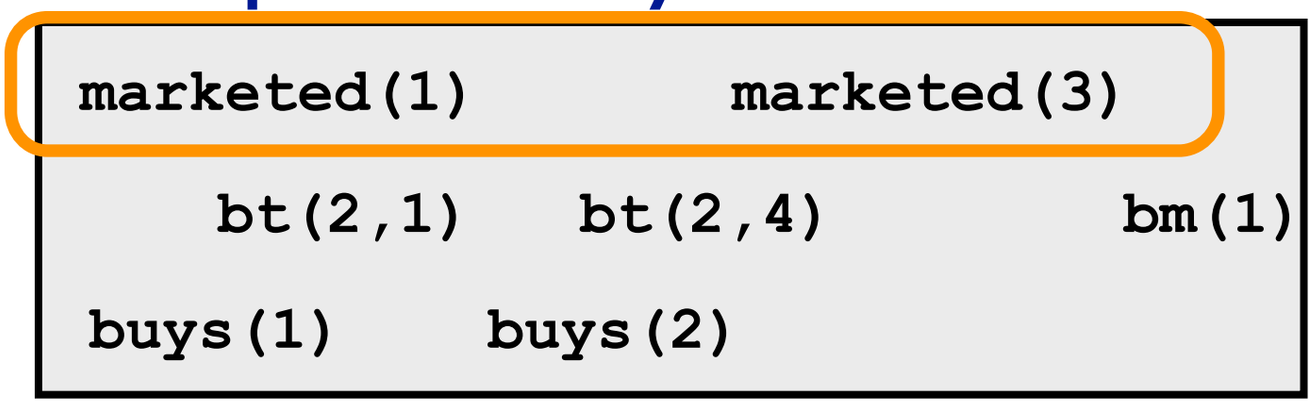



```
person(1).
person(2).
person(3).
person(4).
```

```
buys(P) => 5 :- person(P).
marketed(P) => -3 :- person(P).
```

utility = −3 + −3 + 5 + 5 = 4

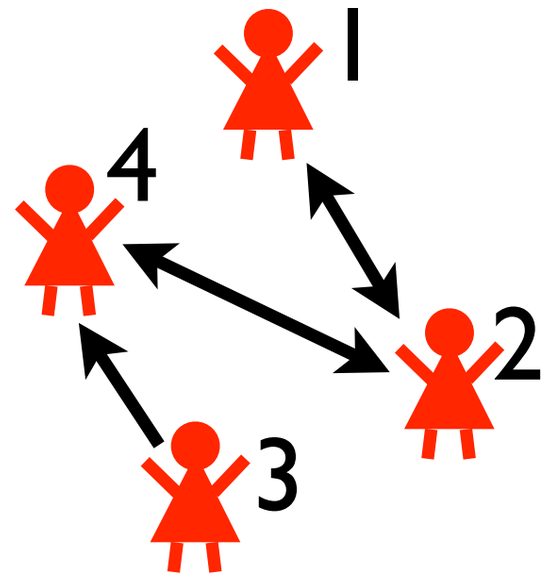
probability = 0.0032




```
friend(1,2).
friend(2,1).
friend(2,4).
friend(3,4).
friend(4,2).
```

world contributes 0.0032×4 to expected utility of strategy

DTProbLog




```
? :: marketed(P) :- person(P).

0.3 :: buy_trust(X,Y) :- friend(X,Y).
0.2 :: buy_marketing(P) :- person(P).

buys(X) :- friend(X,Y), buys(Y), buy_trust(X,Y).
buys(X) :- marketed(X), buy_marketing(X).
```

```
person(1).
person(2).
person(3).
person(4).
```

```
buys(P) => 5 :- person(P).
marketed(P) => -3 :- person(P).
```

```
friend(1,2).
friend(2,1).
friend(2,4).
friend(3,4).
friend(4,2).
```

task: find strategy that maximizes expected utility
solution: using ProbLog technology

A true application

A tool for Computational Biology

Based on decision theoretic variation of ProbLog

ProbLog / Prob. Programming for prototyping

More specialised inference engine was needed

also some special purpose approximations

Probabilistic Rule learning

Information Extraction in NELL

Recently-Learned Facts twitter

Refresh

instance	iteration	date learned	confidence
kelly_andrews is a female	826	29-mar-2014	98.7
investment_next_year is an economic sector	829	10-apr-2014	95.3
shibenik is a geopolitical entity that is an organization	829	10-apr-2014	97.2
quality_web_design_work is a character trait	826	29-mar-2014	91.0
mercedes_benz_cls_by_carlsson is an automobile manufacturer	829	10-apr-2014	95.2
social_work is an academic program at the university rutgers_university	827	02-apr-2014	93.8
dante wrote the book the_divine_comedy	826	29-mar-2014	93.8
willie_aames was born in the city los_angeles	831	16-apr-2014	100.0
kitt_peak is a mountain in the state or province arizona	831	16-apr-2014	96.9
greenwich is a park in the city london	831	16-apr-2014	100.0

instances for many different relations

degree of certainty

NELL: http://rtw.ml.cmu.edu/rtw/

Rule learning in NELL (1)

- Original approach
  - Make probabilistic data deterministic
  - run classic rule-learner (variant of FOIL)
  - re-introduce probabilities on learned rules and predict

Rule learning in NELL (2)

- Newer Page Rank Based Approach (Cohen et al.) -- ProPPR
  - Change the underlying model, from random graph / database to random walk one;
  - No longer "degree of belief" assigned to facts;
  - more like stochastic logic programs
  - Learn rules / parameters

Probabilistic Rule Learning

- Learn the rules directly in a PLP setting
- Generalize relational learning and inductive logic programming directly towards probabilistic setting
- Traditional rule learning/ILP as a special case
- Apply to probabilistic databases like NELL
- ILP 10, IJCAI 15

Pro Log

surfing(X) :- not pop(X) and windok(X).

H

surfing(X) :- not pop(X) and sunshine(X).

pop(e1). windok(e1). sunshine(e1). **B**

?-surfing(e1). **e**
no

B U H |=\= e (H does not cover e)

An ILP example

ProbLog

a probabilistic Prolog

p1:: surfing(X) :- not pop(X) and windok(X).

H

p2:: surfing(X) :- not pop(X) and sunshine(X).

0.2::pop(e1). 0.7::windok(e1). 0.6::sunshine(e1). **B**

?-P(surfing(e1)).**e**

gives (1-0.2) x 0.7 x p1 + (1-0.2) x 0.6 x (1-0.7) x p2 = P(B U H |= e)

not pop x windok x p1 + not pop x sunshine x (not windok) x p1

probability that the example is covered

Inductive Probabilistic Logic Programs

Given

a set of example facts e ∈ E together with the probability p that they hold

a background theory B in ProbLog

a hypothesis space L (a set of clauses)

Find

$$\arg\min_H loss(H, B, E) = \arg\min_H \sum_{e_i \in E} |P_s(B \cup H \models e) - p_i|$$

Observations

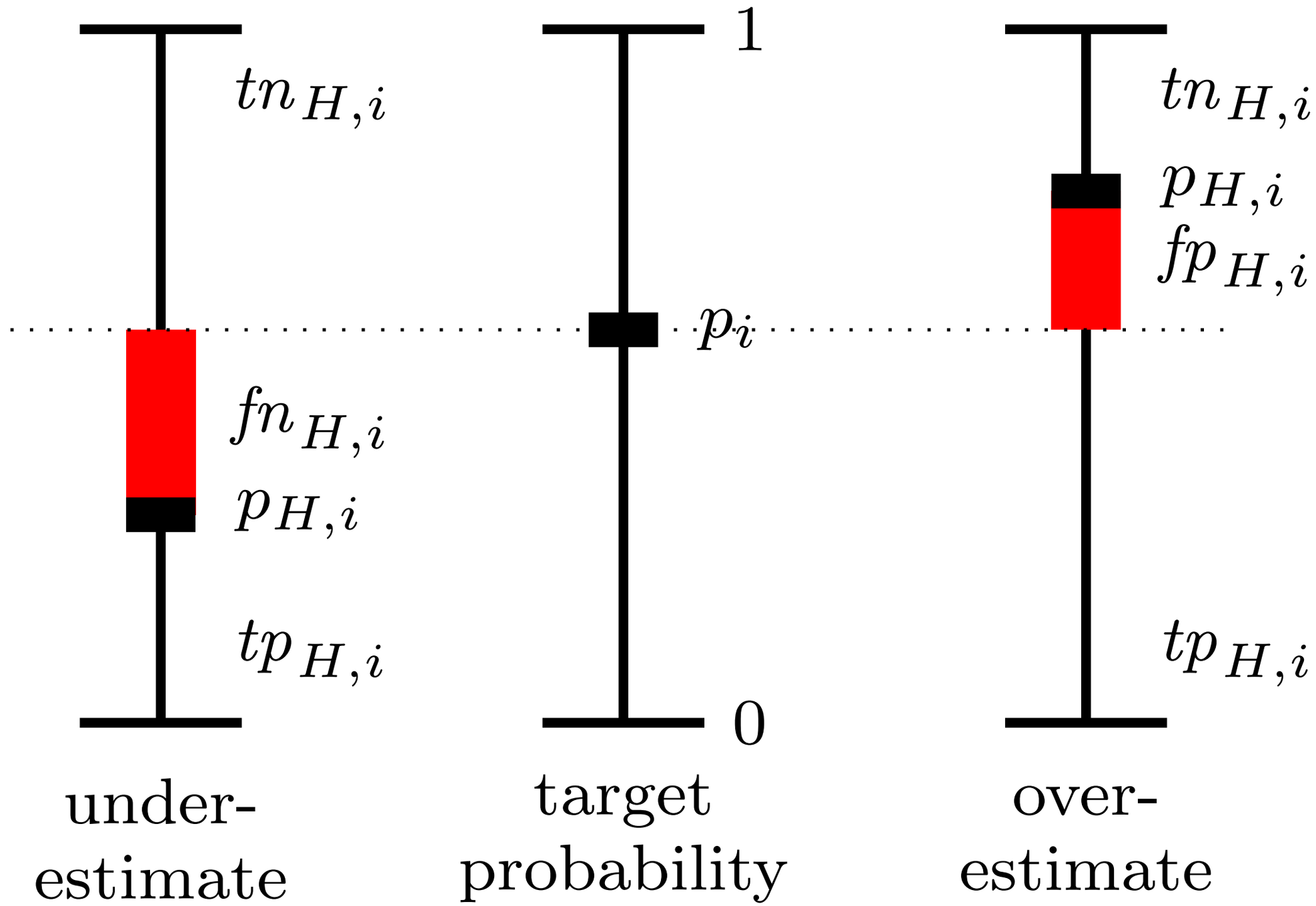
Propositional versus first order

- traditional rule learning = propositional
- inductive logic programming = first order

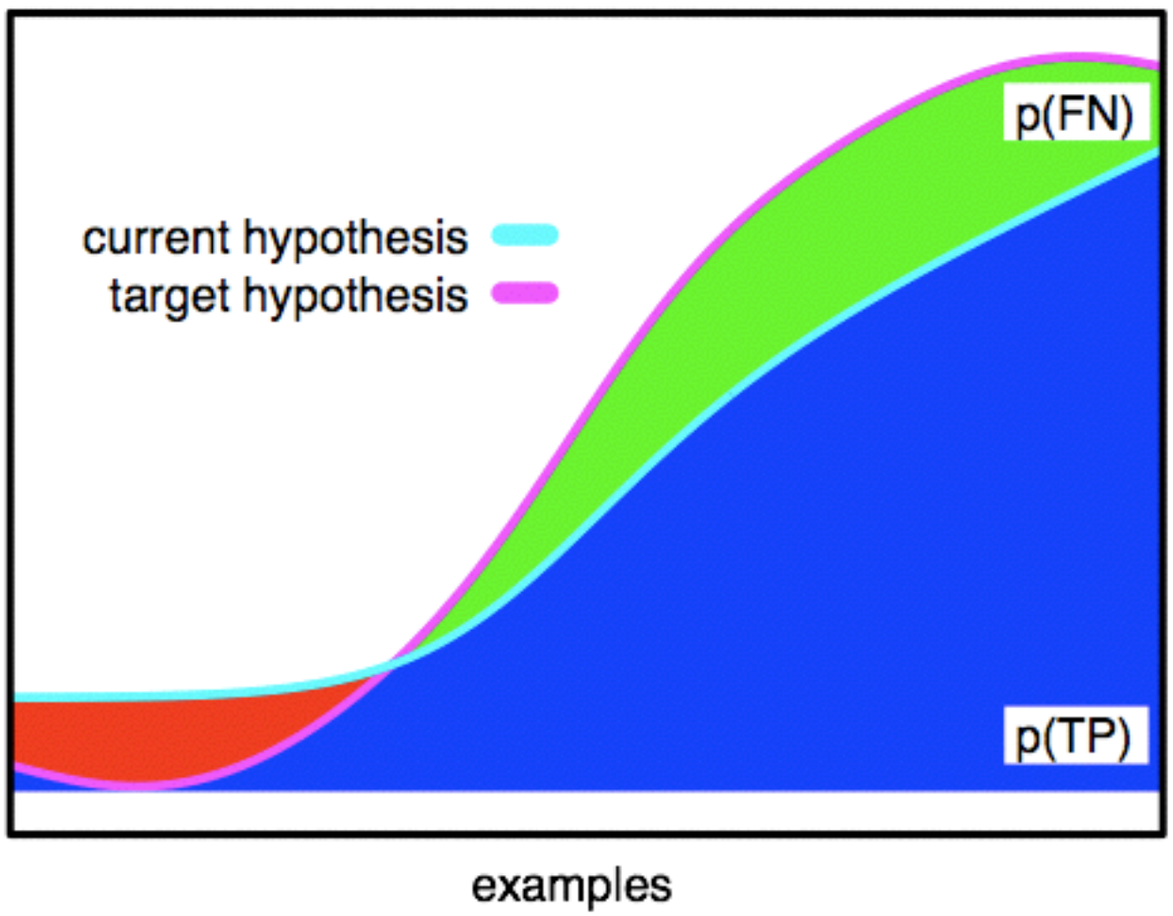
Deterministic case

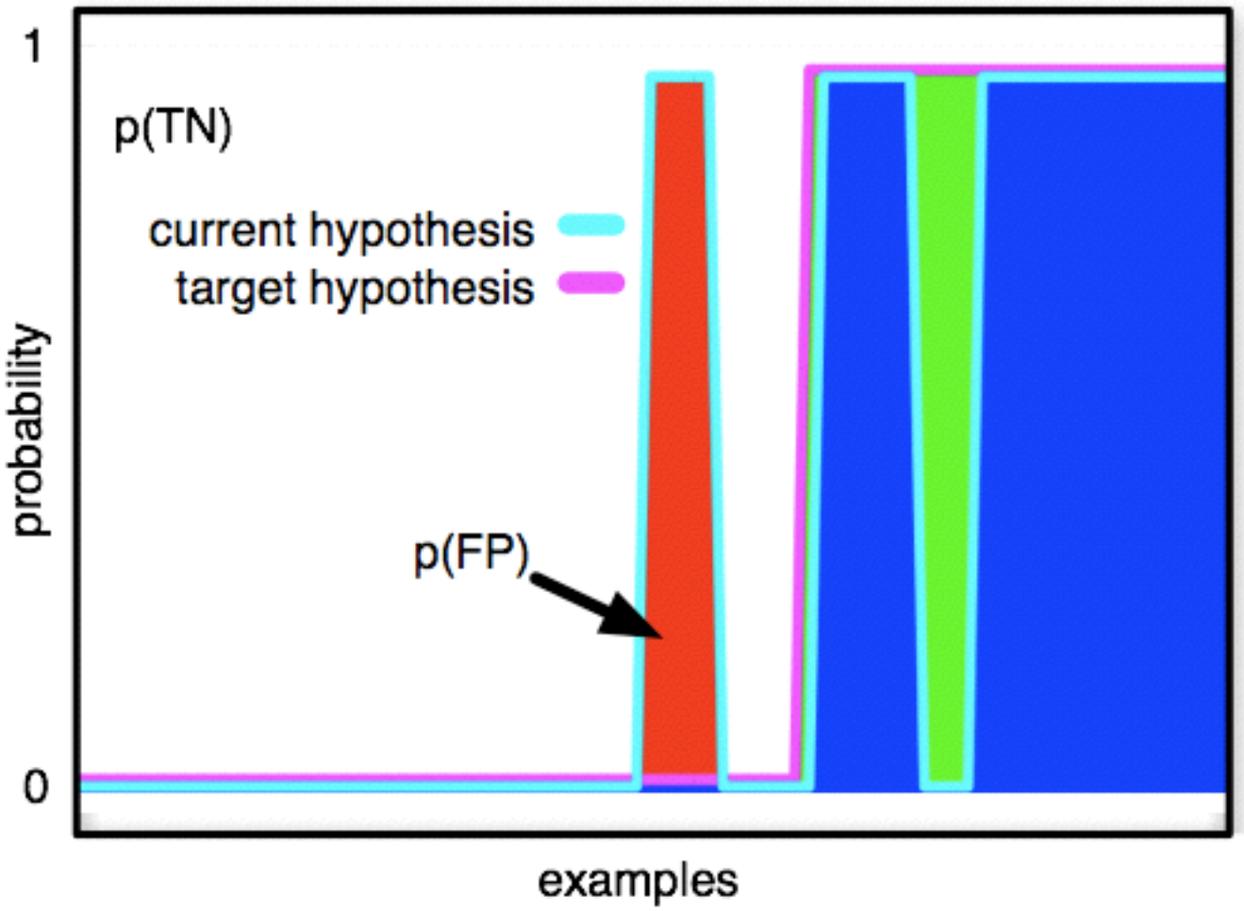
- all probabilities 0 or 1
- traditional rule learning / ILP as special case

Analysis


$tn_{H,i}$
$fn_{H,i}$
$p_{H,i}$
$tp_{H,i}$
under-estimate
1
p_i
0
target probability
$tn_{H,i}$
$p_{H,i}$
$fp_{H,i}$
$tp_{H,i}$
over-estimate

Analysis


p(FN)
current hypothesis
target hypothesis
p(TP)
examples


1
p(TN)
current hypothesis
target hypothesis
probability
p(FP)
0
examples

Rule learning

Interesting properties

- adding a rule is monotonic, this can only increase the probability of an example
- adding a condition to a rule is anti-monotonic, this can only decrease the probability of an example
- several rules may be needed to cover an example
  - use all examples all of the time (do not delete them while learning), do not forget the positives
  - disjoint sum problem

ProbFOIL

Quinlan's well-known FOIL algorithm combined with ProbLog and probabilistic examples and background knowledge

Essentially a vanilla sequential covering algorithm with m-estimate as local score and accuracy as global score.

Criteria

$$precision = \frac{TP}{TP+FP}$$

$$m\text{-}estimate = \frac{TP + m \cdot \frac{P}{N}}{TP+FP+m}$$

local score

$$recall = \frac{TP}{TP+FN}$$

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

global score

Avoiding overfitting using significance test

ProbFOIL

Algorithm 1 The ProbFOIL$^+$ learning algorithm

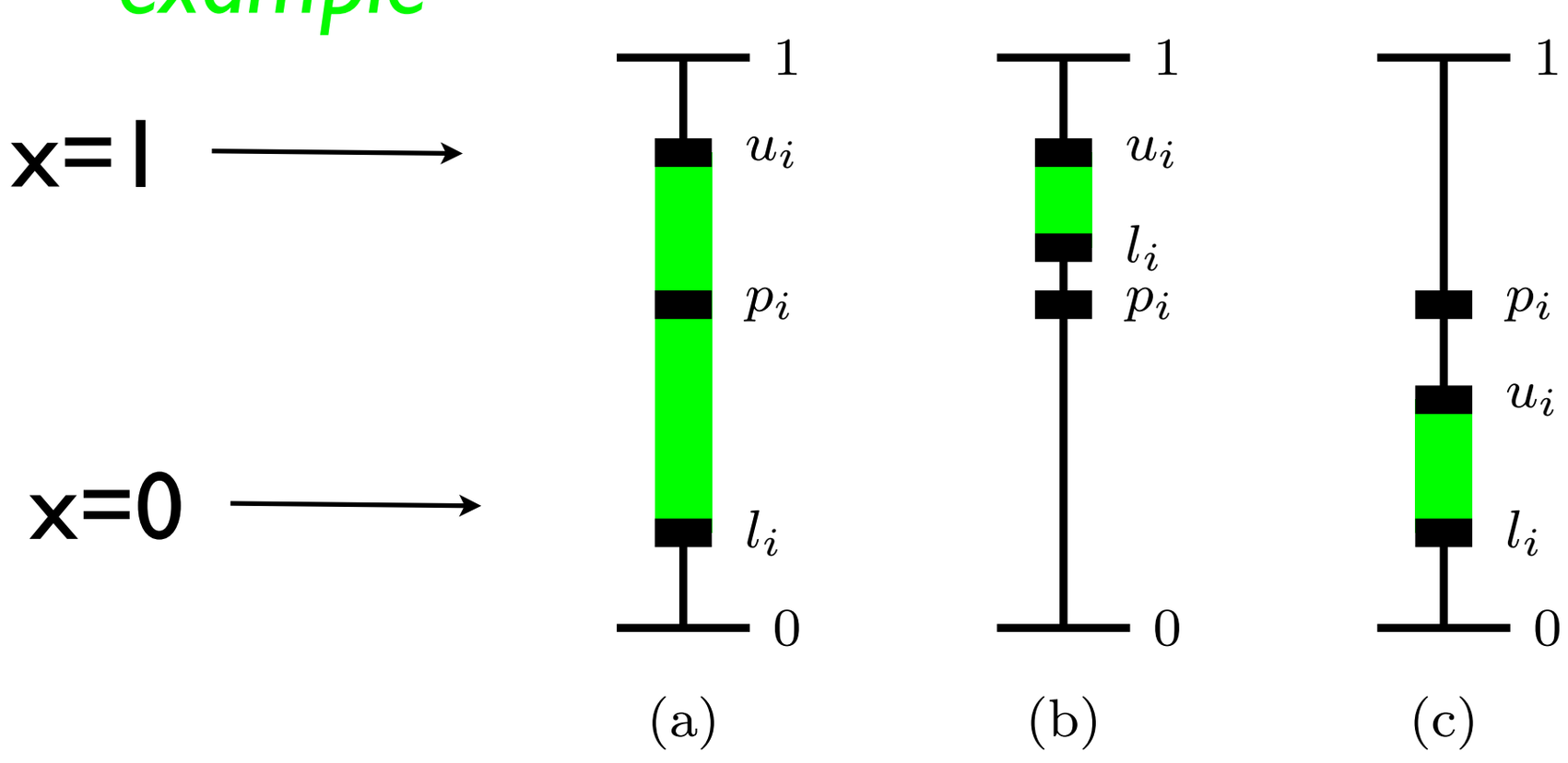
```
1: function ProbFOIL+(target)                                   ▷ target is the target predicate
2:     H := ∅
3:     while true do
4:         clause := LearnRule(H, target)
5:         if GlobalScore(H) < GlobalScore(H ∪ {clause}) then
6:             H := H ∪ {clause}
7:         else
8:             return H
9: function LearnRule(H, target)
10:    candidates := {x :: target ← true}                       ▷ Start with an empty (probabilistic) body
11:    bestrule := (x :: target ← true)
12:    while candidates ≠ ∅ do                                  ▷ Grow rule
13:        nextcandidates := ∅
14:        for all x :: target ← body ∈ candidates do
15:            for all literal ∈ ρ(target ← body) do            ▷ Generate all refinements
16:                if not RejectRefinement(H, bestrule, x :: target ← body) then   ▷ Reject unsuited
   refinements
17:                    nextcandidates := nextcandidates ∪ {x :: target ← body ∧ l}
18:                    if LocalScore (H, x :: target ← body ∧ literal) > LocalScore(H, bestrule) then
19:                        bestrule := (x :: target ← body ∧ literal)   ▷ Update best rule
20:        candidates := nextcandidates
21:    return bestrule
```

Extended rule learning

Learn rules with probability *x*:: *head* :- *body*

What changes ?

- value of *x* *determines prob. of coverage of example*



Extended rule learning

Express local score as a function of *x*

Compute optimal value of *x*

NELL

Table 5: Number of facts per predicate (NELL athlete dataset)

athletecoach(person,person)	18	athleteplaysforteam(person,team)	721
athleteplayssport(person,sport)	1921	teamplaysinleague(team,league)	1085
athleteplaysinleague(person,league)	872	athletealsoknownas(person,name)	17
coachesinleague(person,league)	93	coachesteam(person,team)	132
teamhomestadium(team,stadium)	198	teamplayssport(team,sport)	359
athleteplayssportsteamposition(person,position)	255	athletehomestadium(person,stadium)	187
athlete(person)	1909	attraction(stadium)	2
coach(person)	624	female(person)	2
male(person)	7	hobby(sport)	5
organization(league)	1	person(person)	2
personafrica(person)	1	personasia(person)	4
personaustralia(person)	22	personcanada(person)	1
personeurope(person)	1	personmexico(person)	108
personus(person)	6	sport(sport)	36
sportsleague(league)	18	sportsteam(team)	1330
sportsteamposition(position)	22	stadiumoreventvenue(stadium)	171

athleteplaysforteam

athleteplaysforteam(A,B) :- coachesteam(A,B).
0.875::athleteplaysforteam(A,B) :- teamhomestadium(B,C), athletehomestadium(A,C).
0.99080::athleteplaysforteam(A,B) :- teamhomestadium(B,_), male(A), athleteplayssport(A,_).
0.75::athleteplaysforteam(A,B) :- teamhomestadium(B,_), athleteplaysinleague(A,C), teamplaysinleague(B,C), athlete(A).
0.75::athleteplaysforteam(A,B) :- teamplayssport(B,C), athleteplayssport(A,C), coach(A), teamplaysinleague(B,_).
0.97555::athleteplaysforteam(A,B) :- personus(A), teamplayssport(B,_).
0.762::athleteplaysforteam(A,B) :- teamplayssport(B,C), athleteplayssport(A,C), personmexico(A), teamplaysinleague(B,_).
0.52571::athleteplaysforteam(A,B) :- teamplayssport(B,C), athleteplayssport(A,C), athleteplaysinleague(A,_), teamplaysinleague(B,_), athlete(A), teamplayssport(B,C).
0.50546::athleteplaysforteam(A,B) :- teamplayssport(B,_), teamplaysinleague(B,C), athleteplaysinleague(A,C), athleteplayssport(A,_).
0.50::athleteplaysforteam(A,B) :- teamplayssport(B,_), teamplaysinleague(B,C), athleteplaysinleague(A,C).
0.52941::athleteplaysforteam(A,B) :- teamplayssport(B,_), teamhomestadium(B,_), coach(A), teamplaysinleague(B,_).
0.55287::athleteplaysforteam(A,B) :- teamplayssport(B,_), teamplaysinleague(B,C), athleteplaysinleague(A,C), athlete(A).
0.46875::athleteplaysforteam(A,B) :- teamplayssport(B,_), teamplaysinleague(B,_), coach(A), teamhomestadium(B,_).

Experiments

Table 4: Precision for different experimental setups and parameters (A: $m = 1, p = 0.99$, B: $m = 1000, p = 0.90$).

Setting	**athleteplaysforteam**		**athleteplayssport**		**teamplaysinleague**		**athleteplaysinleague**		**teamplaysagainstteam**	
train/test/rule	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**	**A**	**B**
1: det/det/det	74.00	69.36	94.14	93.47	96.29	82.15	80.95	74.14	73.40	73.86
2: det/prob/det	73.51	69.57	97.53	94.85	96.70	87.83	90.83	77.73	73.70	73.35
3: det/prob/prob	74.67	69.82	95.86	94.74	96.35	82.57	82.26	75.29	73.84	74.34
4: det/prob/prob	77.25	73.87	96.53	96.04	98.00	90.59	84.91	79.36	77.26	77.83
5: det/prob/prob	74.76	69.97	95.85	94.69	96.44	82.51	81.99	75.07	73.90	74.16
6: prob/prob/det	75.83	73.11	93.40	93.76	94.44	93.67	79.41	79.42	80.87	80.60
7: prob/prob/prob	78.31	73.72	95.62	95.10	98.84	91.86	96.94	79.49	85.78	81.81

Table 3: Learned relational rules for the different predicates (fold 1).

0.9375::athleteplaysforteam(A,B)	←	athleteledsportsteam(A,B).
0.9675::athleteplaysforteam(A,B)	←	athleteledsportsteam(A,V1), teamplaysagainstteam(B,V1).
0.9375::athleteplaysforteam(A,B)	←	athleteplayssport(A,V1), teamplayssport(B,V1).
0.5109::athleteplaysforteam(A,B)	←	athleteplaysinleague(A,V1), teamplaysinleague(B,V1).
0.9070::athleteplayssport(A,B)	←	athleteledsportsteam(A,V2), teamalsoknownas(V2,V1), teamplayssport(V1,B), teamplayssport(V2,B).
0.9070::athleteplayssport(A,B)	←	athleteplaysforteam(A,V2), teamalsoknownas(V2,V1), teamplayssport(V1,B), teamplayssport(V2,B),teamalsoknownas(V1,V2).
0.9070::athleteplayssport(A,B)	←	athleteplaysforteam(A,V1), teamplayssport(V1,B).
0.9286::athleteplaysinleague(A,B)	←	athleteledsportsteam(A,V1), teamplaysinleague(V1,B).
0.7868::athleteplaysinleague(A,B)	←	athleteplaysforteam(A,V2), teamalsoknownas(V2,V1), teamplaysinleague(V1,B).
0.9384::athleteplaysinleague(A,B)	←	athleteplayssport(A,V2), athleteplayssport(V1,V2), teamplaysinleague(V1,B).
0.9024::athleteplaysinleague(A,B)	←	athleteplaysforteam(A,V1), teamplaysinleague(V1,B).

Contributions

Learning rules (or inducing logic programs) from uncertain/ probabilistic data

A new problem formulation

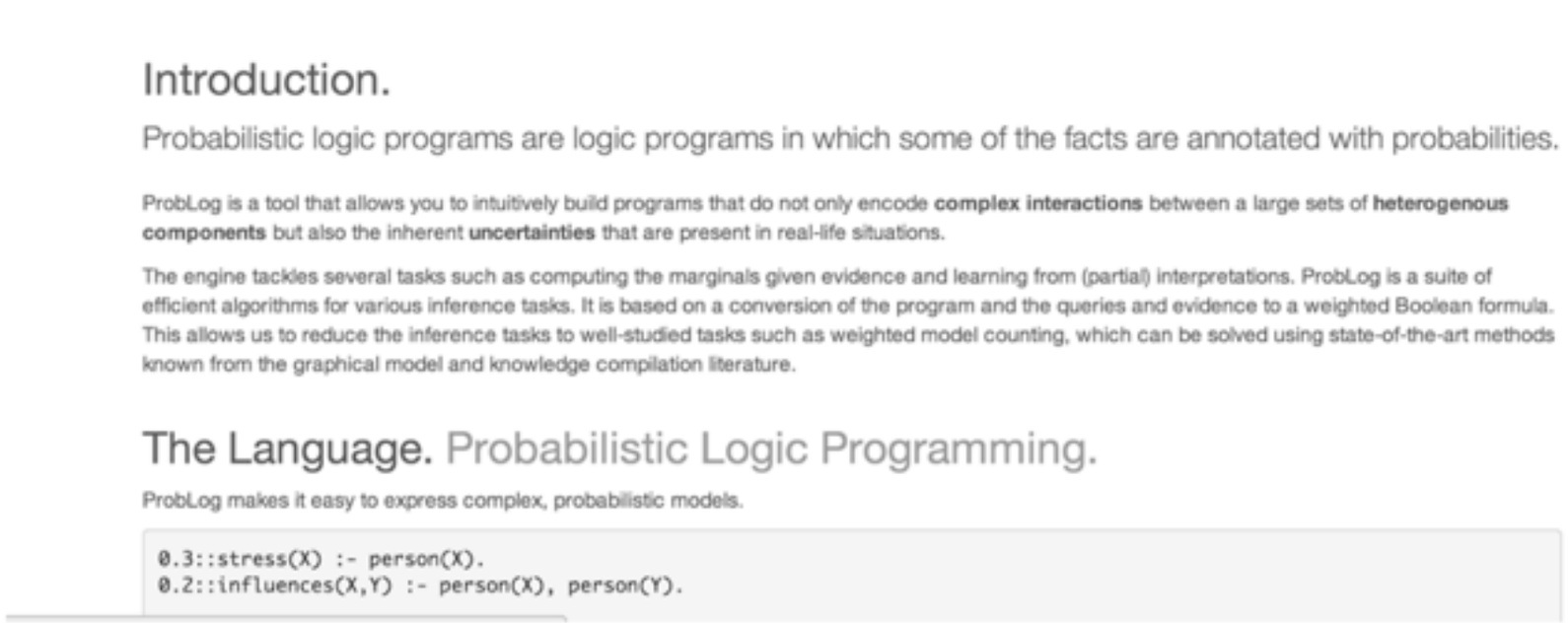
Traditional rule learning (ILP) is the deterministic special case

Traditional rule learning principles apply directly (including ROC analysis)

Maurice Bruynooghe
Bart Demoen
Anton Dries
Daan Fierens
Jason Filippou
Bernd Gutmann
Manfred Jaeger
Gerda Janssens
Kristian Kersting
Angelika Kimmig
Theofrastos Mantadelis
Wannes Meert
Bogdan Moldovan
Siegfried Nijssen
Davide Nitti
Joris Renkens
Kate Revoredo
Ricardo Rocha
Vitor Santos Costa
Dimitar Shterionov
Ingo Thon
Hannu Toivonen
Guy Van den Broeck
Mathias Verbeke
Jonas Vlasselaer

Thanks !

http://dtai.cs.kuleuven.be/problog



PLP Systems

- **PRISM** http://sato-www.cs.titech.ac.jp/prism/
- **ProbLog2** http://dtai.cs.kuleuven.be/problog/
- Yap Prolog http://www.dcc.fc.up.pt/~vsc/Yap/ includes
  - **ProbLog1**
  - **cplint** https://sites.google.com/a/unife.it/ml/cplint
  - **CLP(BN)**
  - **LP2**
- **PITA** in XSB Prolog http://xsb.sourceforge.net/
- **AILog2** http://artint.info/code/ailog/ailog2.html
- **SLPs** http://stoics.org.uk/~nicos/sware/pepl
- **contdist** http://www.cs.sunysb.edu/~cram/contdist/
- **DC** https://code.google.com/p/distributional-clauses
- **WFOMC** http://dtai.cs.kuleuven.be/ml/systems/wfomc

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